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The impact of perceived crisis severity on intention to use voluntary proximity tracing applications

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ABSTRACT

During a crisis such as COVID-19, governments ask citizens to adopt various precautionary behaviours, such as using a voluntary proximity tracing application (PTA) for smartphones. However, the willingness of individual citizens to use such an app is crucial. Crisis decision theory can be used to better understand how individuals assess the severity of the crisis and how they decide whether or not to adopt the precautionary behaviour. We propose a research model to examine the direct influence of perceived crisis severity on intention to use the technology, as well as the indirect impact via PTAs’ benefits for citizens. Exploratory and confirmatory factor analyses confirm the two dimensions of the benefits, namely personal and societal benefits. We used PLS-MGA to evaluate our research model. The results confirm the influence of the perceived severity of COVID-19 on the intention to use the PTA, as well as the mediating effects of personal and societal benefits on this relationship. Our findings contribute to the technology adoption literature and showcase the use of crisis decision theory in the field of information systems.

1. Introduction

Crises take many forms, including natural disasters, terrorist attacks, international conflicts, economic collapses, civil unrest, and pandemics (Chen et al., 2020). Pandemics can cause great harm, both in terms of personal restrictions and broader societal consequences (Beauvoyer, Dupéré, & Guitton, 2020; Guitton, 2020; Vaughan, 2011). Due to the COVID-19 pandemic crisis, governments have introduced many precautionary restrictions that have changed the lives of citizens (Klein & Busis, 2020; Pan, Cui, & Qian, 2020; Riemer, Ciriello, Peter, & Schlagwein, 2020).

One strategy used to limit the spread of infectious diseases is proximity tracing. Proximity tracing is a process of identifying, assessing, and managing individuals who have been exposed to a disease to prevent further transmission (OECD, 2020). Mobile technologies can help capture, share, process, and access proximity information (Laukken, 2019; Mehmood et al., 2019; Sakurai & Murayama, 2019; Sharma & Kshetri, 2020). Proximity tracing applications (PTAs) for smartphones have been ranked among the top ten disruptive technologies to be adopted globally in 2021 (Johnson, 2020; Landrein, 2021). Recently, it has been established through modelling, statistical analysis and experiments that higher PTA adoption rates can significantly reduce the number of cases during an epidemic outbreak (Kahnbach et al., 2021; Rodríguez et al., 2021; Wymant et al., 2021). However, the number of users of voluntary PTAs remains relatively low (LibertiesEU, 2021; Rowe, 2020). These apps will succeed only if they create critical mass by demonstrating immediate value (Farronato et al., 2020).

A limited number of studies focus on technology adoption during crises when individuals must make decisions in complex and dynamic situations that require a response with which they are unfamiliar or lack experience (Dionne, Gooty, Yammarino, & Sayama, 2018). Although there are many studies in the area of e-health adoption (Cimperman, Makovec Brenčič, & Trkman, 2016; Scott Kruse et al., 2018), study of mobile applications in crisis is still a developing field of research. While the typical factors influencing technology adoption are well known (Karahanna, Straub, & Chervany, 1999; Venkatesh & Davis, 2000), PTA adoption is a novel situation, and further research on influencing constructs is needed (Laukken, 2019; Pan & Zhang, 2020; Shiau, Yan, & Lin, 2019).

Previous literature on PTA adoption has overlooked the influence of perceived crisis severity on the intention to use the technology. According to crisis decision theory, perceived crisis severity plays a...
significant role in the adoption of precautionary behaviours. When individuals consider whether to use a PTA, they assess the potential benefits of the PTA to their other interests. This paper defines personal and societal benefits to investigate the impact of these interests. Although the personal benefits associated with the use of PTAs have already been studied (Qazi et al., 2020), measurement of the societal benefits of PTAs has been neglected (Trang, Trenz, Weiger, Tarafdar, & Cheung, 2020).

The goal of our work is to provide a better understanding of the relationship between perceived crisis severity and the behavioural intention to use PTAs and the impact that personal and societal benefits have on that relationship. We used tenets of crisis decision theory (1) to understand the impact of perceived severity of COVID-19 and (2) to explain the link between the severity and the acceptance of a precautionary behaviour. We tested our research model on 401 citizens of a Western country in May 2020 and on another 800 residents of the same country in March 2021. The results confirmed that perceived crisis severity, personal benefits and societal benefits significantly predicted intention to use PTAs.

The paper is organised as follows. Section 2 explains how crisis decision theory can be used to better understand the adoption of a technology during a crisis. Then, the adoption problem of voluntary PTAs for smartphones is presented and the relevance of the technology’s benefits is elaborated. Two dimensions of the benefits of PTAs are defined, namely societal and personal benefits. Section 3 theorises the hypotheses using crisis decision theory and both behaviour and adoption literature. Section 4 presents the research methodology used to develop a scale to measure PTAs’ benefits for citizens and present partial least squares (PLS) multi-group analysis (MGA) results. Section 5 discusses hypotheses results, along with theoretical and practical implications. Section 6 presents limitations and suggests avenues for future work. Section 7 provides concluding remarks.

2. Background and motivation for the study

2.1. Crisis decision theory

Crisis decision theory provides a framework understand how individuals evaluate and respond to crisis (Sweeney, 2008). The theory integrates literatures on coping, health behaviours, and decision making. People are advised to perform a set of precautionary behaviours before, during, and after a crisis (Wong & Sam, 2011). However, people’s unwillingness to adopt them is a major challenge to minimising the spread of COVID-19 in their countries (Rowe, 2020). The restrictions limited freedom of movement (Barnes, 2020; Klein & Busis, 2020) and required transition to a “new normal” (Barnes, 2020; Qazi et al., 2020), with closed restaurants, cancelled transportation, limited outdoor activities, and banned crowd gathering for extended periods of time (Appendix A). In addition, COVID-19 caused severe harm to society (Pan et al., 2020) by limiting public health safety, general safety, and the performance of the national economy while increasing alienation (Appendix A). Consequently, COVID-19 caused many negative emotions such as fear, stress, anxiety, depression, loneliness, worry, and guilt (Barnes, 2020; Kraemer et al., 2020; Van Bavel, Baicker, Boggio, & Capraro, 2020; Wang et al., 2020) and will most likely continue to cause problems in the future.

2.1.2. The link between perceived crisis severity and desired precautionary behaviour

Once people assess severity, they begin to assess response by focusing on (a) the resources required to carry out the response, (b) the direct consequences of the response, and (c) the indirect consequences of the response (Sweeney, 2008). Resources required for a response can include money, time, energy, and physical strength. A reaction can have both positive and negative consequences. Our paper focuses exclusively on the positive consequences of the response behaviour.

Positive direct consequences of behaviour are the results that change the status of the crisis for the better. Individuals focus on the problem at hand, namely the disease, and estimate the following: the likelihood that adopting the precautionary behaviour would lead to a positive change and the possibility that they can change their minds at a later point of time. Further, the positive indirect consequences can lead to changes not only in the status of the crisis but also in other aspects of the individuals’ lives. Consequently, the indirect consequences of a response are not necessarily less important than the direct ones. Moreover, they can have an impact on different areas of the individuals’ lives and/or other people in society. Table 1 shows the use crisis decision theory to make predictions about desired precautionary behaviour.

2.2. Adoption of voluntary proximity tracing applications for smartphones

Citizens can respond to COVID-19 crisis with many precautionary behaviours, such as wearing masks, washing hands, adhering to restrictions, getting tested, and self-isolating (Salathe et al., 2020). Our study focuses on the use of PTAs for smartphones. Western governments have encouraged their citizens to use PTAs on a voluntary basis. By giving citizens the freedom of choice, governments share with citizens the responsibility of limiting the spread of COVID-19 in their countries (Rowe, 2020).

East Asia is a notable example of how mandatory use of PTAs can slow COVID-19 down (Huang, Sun, & Sui, 2020). However, voluntary PTA adoption in Western society is much lower (LibertiesEU, 2021). In Iceland, the adoption rate is 40% (Johnson, 2020), in Germany 20% (Jee, 2020), in United Kingdom 3% and in Australia also 3% (Taylor, 2021). PTA adoption in Austria, France (Rowe, 2020), and Norway (Jee, 2020)
Studies that incorporate these factors are still in their infancy (Walrave, Waeterloos, 2020) has already been deemed to have failed. Even Iceland, which has the highest adoption rate, reports that their PTA has not helped much (Johnson, 2020).

Intention to use a technology is defined as the degree to which an individual perceives their willingness to use the application (Yu, 2012). Table 2 compares our study with previous studies that have similar data analysis and rigour and focus on better understanding citizens’ intention to use PTAs. Although several studies have examined the effect of digital and manual contact tracing on reducing the effective reproductive number and on how technology affects digital contact tracing effectiveness (Grekosikis & Liu, 2021), few studies examine the influence of the perceived severity of COVID-19 and the benefits of using PTA. Studies that incorporate these factors are still in their infancy (Walrave, Waeterloos, & Ponnet, 2020).

The role of crisis decision theory in individuals’ assessments of possible responses to a precautionary behaviour.

### Table 1

| Focus of the assessment | Description | Hypo. |
|-------------------------|-------------|-------|
| Resources required for a response | Individuals consider cost in money, time, energy, and physical strength. | / |
| Positive consequences of a response Direct | Individuals focus on the problem at hand with the related emotions and assess the following: - the likelihood that the precautionary behaviour response would lead to positive change; - the possibility of making a different response choice later. | H1 |
| Indirect | Consequences for other areas of individuals’ lives accompanied with the related emotions. | H2 |
| Indirect | Consequences for others, accompanied by the related emotions. | H3 |
| Consequences for individuals’ public image with the related emotions | / |
| Negative consequences of a response Direct | (Out of scope of our paper.) | / |
| Indirect | / |

### Table 2

Similar studies on PTA adoption.

| (Sharma et al., 2020) | (Velicia-Martin, Cabrera-Sanchez, Gil-Cordero, & Palos-Sanchez, 2021) | (Hassandoust, Akhalghpour, & Johnston, 2021) | (Walrave, Waeterloos, & Ponnet, 2021) | Our study |
|-----------------------|-------------------------------------------------|-------------------------------------------------|-------------------------------------------------|---------|
| Perceived severity in context of COVID-19 | No | No | No | No |
| Benefits of PTA (Behaviour) intention to use PTA | No | No | Yes | Yes |
| Number of all constructs in the research model (without control variables) | 13 | 7 | 13 | 8 |
| Theory/model used | Procedural fairness theory, dual calculus theory, protection motivation theory, theory of planned behaviour, and Hofstede’s cultural dimension theory | Technology acceptance model | Privacy calculus theory | Extended unified theory of acceptance and use of technology model |
| Respondents | Fiji | United Kingdom | United States | Belgium |
| Analyses | SEM | SEM-MGA | SEM | SEM-MGA |

SEM, structural equation modelling; MGA, multigroup analyses.

2.3. The relevance of technology’s benefits and the need to examine PTAs’ benefits for citizens

Perceptions of technology as beneficial and useful have strong predictive power in the technology adoption literature (Cimperman et al., 2016). The role of benefits in technology adoption has been widely studied in the information systems research domain (Fischer, Putzke-Hattori, & Fischbach, 2019). Davis (1989) defined perceived usefulness as the extent to which a person believes that using a particular system would improve his or her job performance. Improved job performance is rewarded with benefits such as bonuses, raises, promotions, and rewards and is thus an example of extrinsic motivation (Davis, Bagozzi, & Warshaw, 1992). Over the years, several studies have identified perceived usefulness as a large predictor of intention to use a technology (Bitler, Hoynes, & Schanzenbach, 2020; Hanafizadeh, Behboud, Koshksaray, & Tabar, 2014; Venkatesh & Morris, 2000; Venkatesh & Davis, 2006). Previous studies have reported positive effects of mobile technology adoption (e.g., Hanafizadeh et al., 2014). One of the most well-known extensions of the technology adoption model is the unified theory of acceptance and use of technology (Venkatesh, Morris, Davis, & Davis, 2003). The new model introduced the construct performance expectancy, which is similar to perceived usefulness and is defined as the degree to which an individual believes that using the system will help him or her to attain gains in job performance (Venkatesh et al., 2003). Previous literature reports positive association of performance expectancy with health technology adoption (Cimperman et al., 2016; de Veer et al., 2015).

PTAs can improve public health performance by minimising new infections and individual health performance by minimising opportunities for proximity with infected individuals. Moreover, PTAs can also protect other interests of citizens. PTAs’ benefits for citizens include better public health safety, increased overall safety, improved performance of the national economy, better social life (less alienation), and performing activities such as eating and drinking outdoors, using transportation, being outdoor, and being in crowds (Appendix A). These benefits of PTAs can strongly influence the intention to use a PTA and need further attention.

2.4. Dimensions of PTAs’ benefits for citizens: personal and societal

Previously, Barnes (2020) examined the impact of COVID-19 on enhanced use of technologies for telework, e-health, e-education,
e-commerce, and e-wellbeing. Similar to our research, Trang et al. (2020) and Klein and Buis (2020) focused on e-health and discussed the potential of technologies to deliver benefits to both individuals and society. The successful use of technologies such as PTAs can secure the PTAs’ benefits for citizens, which are believed to have two dimensions, namely personal and societal benefits (Trang et al., 2020). We propose the following definitions of the two dimensions that define our two constructs for further investigation:

- **Personal benefits (PBs)** refer to the extent to which a citizen believes that using a PTA would help secure his or her regular daily routine, which is threatened by COVID-19 restrictions, such as the government’s prohibition on eating and drinking outdoors, travelling, being in crowds, and being outdoors.

- **Societal benefits (SBs)** refer to the extent to which a person believes that the use of a PTA would support the common good of people in society threatened by COVID-19 restrictions, such as endangering public health and general safety of society, slowing national economic performance, and alienating individuals.

3. Theoretical framework and hypothesis development

3.1. Direct impact of perceived crisis severity on intention to use

Many countries promote the use of PTAs, emphasizing the severity of COVID-19 (Ting, Carin, Dzau, & Wong, 2020). COVID-19 has direct consequences on human health (Sweeney, 2008; Van Bavel et al., 2020) and PTAs were designed to protect that health. Citizens may perceive COVID-19 as sufficiently threatening to their personal health and therefore more inclined to respond by adopting a PTA (Sweeney, 2008; Walrave et al., 2020). Furthermore, there is an additional burden of negative emotions that develop immediately after interpreting the severity of a crisis, such as anger, surprise, worry, and contempt (Choi & Lin, 2009; Dionne et al., 2018), which could motivate citizens to use PTAs. Researchers agree that the fear of having a disease can trigger individual behaviours (Funk et al., 2010; Van Bavel et al., 2020) such as, for example, the use of a PTA.

Previous research has shown that wearable self-tracking devices can improve health (Stiglbauer, Weber, & Batinic, 2019). Precautionary behaviour in the use of PTAs has been shown to significantly limit the spread of COVID-19 (Huang et al., 2020), which may encourage citizens of Western society to trust the capabilities of PTAs. However, there is a high degree of uncertainty as to whether an individual PTA user would personally benefit from its use. By electing to use PTAs, citizens could avoid experiencing the regret of not having done everything possible to limit the virus (Carroll, Sweeney, & Shepperd, 2006). Consistent with previous literature, we propose the following:

**H1.** Citizens’ perceived crisis severity of COVID-19 positively influences their intentions to use voluntary proximity tracing applications for smartphones.

3.2. Mediating role of personal benefits

Crisis decision theory suggests that when assessing how to respond to a precautionary behaviour, people also consider the impact of the response on their lives as a whole, not just the state of the current crisis. The presence of the COVID-19 crisis poses a threat to citizens’ normal daily routines (Karel, Gurrera, Hicken, & Moe, 2010; Sweeney, 2008). Similar to ways mobile health applications can allow patients to satisfy their health care needs (Li, Zhang, Li, & Zhang, 2020), PTAs can help citizens satisfy their need to return to their daily routine. When conditions that prevent the ability to have a normal daily routine are present, individuals are motivated to take action to eliminate their discomfort (Porter, Bigley, Steers, & Steers, 2002), and they may want to reinforce a positive sense of self-efficacy and control over securing/regaining such personal benefits (Van Bavel et al., 2020).

The adoption of any precautionary behaviour is shaped by the individual’s beliefs (Breuer et al., 2004; De Zwart, Veldhuijzen, Richardus, & Brug, 2010; Goodwin et al., 2011), for example, that the decision to use a PTA can have positive indirect effects on everyday life. Indeed, when the disease is under control, the government does not need to restrict citizens’ freedom to eat and drink outdoors, travel, performing outdoor activities, and being in crowds. Previous research confirms that individuals are motivated to accept and use an application if they believe it will benefit them in their daily lives (Hanafizadeh et al., 2014), especially during a pandemic crisis such as COVID (Smith et al., 2019). This leads to the following hypothesis:

**H2.** The relationship between citizens’ perceived crisis severity of COVID-19 and intentions to use voluntary proximity tracing applications for smartphones is positively mediated by the construct personal benefits.

3.3. Mediating role of societal benefits

COVID-19 restrictions have caused many negative consequences for society as a whole (Sweeney, 2008). With a reduced number of infections, society can return to functioning at levels as it did in the times before COVID-19 (Huang et al., 2020). Since PTAs are designed to reduce the number of new infections, society could benefit from their use with better public health, better general safety of society, higher levels of socialisation (less alienation) and better performance of national economies. PTA use is strongly shaped by citizens’ beliefs (Breuer et al., 2004; De Zwart et al., 2010; Goodwin et al., 2011) about whether the PTA can help the society. Individuals who are more convinced of societal benefits are more likely to use the application (Hassandoust et al., 2021; Van Bavel et al., 2020; Walrave et al., 2020).

Cooperation among people in crisis appears to be common during a range of emergencies, and individuals often display remarkable altruism (Van Bavel et al., 2020). Human cooperation is about caring for others in a social group and protecting the group’s common interests (Gintis, Bowles, Boyd, & Fehr, 2006). Citizens may want to use PTAs to enhance their sense of collective self-efficacy (Van Bavel et al., 2020). Empirical literature suggests that individuals have a propensity to cooperate more than would be expected if they have a predisposition to helping others (West, El Mouden, & Gardner, 2011). By sharing information about positive COVID-19 test results via PTAs, users take action to limit the spread of the virus and anonymously demonstrate their care for other citizens. This leads to the following hypothesis:

**H3.** The relationship between citizens’ perceived crisis severity of COVID-19 and intention to adopt voluntary proximity tracing applications for smartphones is positively mediated by the construct societal benefits.

The model is shown in Fig. 1.

4. Methodology

4.1. Data collection

We collected the data set 1 from students at University of Ljubljana. Students were awarded bonus points for their participation. We collected the data set 2 and 3 using the CAWI method with the help of the leading regional marketing agency. The agency is the regional leader in surveying citizens and has almost 20 years of experience, including extensive work with data collection for Slovenia’s National institute of Public Health. It collected data at the end of the third month after the first identified infection in the country (data set 2; group “3 months”), and at the end of the twelfth month (data set 3; group “12 months”). The residents received monetary compensation from the agency, which collected the data. All the respondents fully answered their questionnaires. Data collection details are provided in Table 1.
4.2. PTAs’ benefits for citizens item generation and content validation

We needed to develop the scale to measure the PTAs’ benefits for citizens phenomena. We followed established scale development guidelines and examples (DeVellis, 2003; MacKenzie, Podsakoff, & Podsakoff, 2011; Mimouni-Chaabane & Volle, 2010; Motamarri, Akter, & Yanamandram, 2020). Based on the literature review (summarised in Appendix A), an initial list of the benefits and their representing items was prepared. The PB items were adopted from Qazi et al. (2020), while the SB measurement items were newly proposed. To improve content validity, we discussed the proposed list with three experts who had a Ph. D.s in technology adoption in healthcare. The academics suggested several improvements. We reformulated the items from Qazi et al. (2020) as a positive statement. For example, “Avoid eating out due to COVID-19” became “I believe that using the PTA would enable me to eat and drink out more often”. Additionally, we removed some items, which were judged to be unclear, too general, redundant, or not representative of the domain PTAs’ benefits for citizens. This procedure yielded the final 11 items presented in Table 4. Participants rated each item using a Likert scale with values from 1 (strongly disagree) to 7 (strongly agree) (DeVellis, 2003).

4.3. Exploratory factor analysis

We used dataset 1 to analyse responses to PTAs’ benefits for citizens items using iterated principal axis factoring in RStudio. The first factor captures 52%, while the second explains 13%. Adding a third factor explains only an additional 2% of the total variance. Examination of a scree plot also suggested that the two-dimensional solution. The model with two factors accounts for 64% of the total variance. Oblique rotated factors delivered coefficients that make substantive sense. Correlation between the two factors is 0.59. We also examined correlations between the items and the factors by calculating factor structure coefficients (Table 5). The results show that the PB1-5 items (adapted from Qazi et al., 2020), are relatively highly correlated (ranging from 0.78 to 0.89) with Factor 2, while the newly developed SB1-6 items are highly correlated (ranging from 0.71 and 0.87) with Factor 1. The items’ shared variances (communalities) range from 0.50 to 0.79, which indicates sufficient representation. The item loadings value the factor they represent (ranging from 0.67 to 0.89). The multiple $R^2$ of scores are 0.91 for Factor 1 and 0.93 for Factor 2.

4.4. Confirmatory factor analysis

We performed confirmatory factor analysis on data set 2 with RStudio using the maximum likelihood estimation method. Based on the results from exploratory factor analysis, we related the SB1-6 items to factor SB, and PB1-5 items to factor PB. A two-factor confirmatory factor analysis that allowed correlation between the two factors was performed. The loading values (Table 6) are substantively identical to those generated by the exploratory factor analysis. Correlation between factors SB and PB is 0.821. Fit statistics report that the model fits the data well. Chi-square is 142.806, with a p-value of 0.000 (43 degrees of freedom). The RMSEA value (0.076) falls within the acceptable range of 0.05 and 0.08, while the CFI value (0.982) and TLI value (0.976) meet the recommended levels above 0.95 (Hair, Black, Babin, Andersson, & Tatham, 2006).

4.5. Partial least squares analysis

We treat all constructs from the research model, namely, personal benefits (PBs), societal benefits (SBs), perceived crisis severity (PCS) and intention to use (ITU) as reflective (Table 7). The ITU items were adopted from Alalwan, Dwivedi, and Rana (2017) and Venkatesh et al. (2003), because they were verified and considered in other IT adoption studies, and paraphrased to fit the context of PTAs. Zhou et al.’s (2019) list of PCS items was shortened and paraphrased to fit the context of COVID-19. All items were translated into Slovenian, and measured using a 7-point Likert scale. Additionally, we included one control variable: age group. Since adults above 55 years old are at greatest risk of serious health-related consequences from COVID-19 (Davies et al., 2020), we created and investigated two age groups: one with respondents aged 18–54 and the other with respondents aged 55–74.

We selected Slovenia as a country that is representative of Western society. Slovenia has approximately two million citizens. The government developed its own decentralised PTA called #OstaniZdrav based on the open source Corona-Warn-App. The application was offered to the citizens in the middle of August 2020 (Urad Vlade Republike Slovenije za komuniciranje Government Communication Office, 2020). The application has three functionalities: (1) getting exposure risk assessments, (2) entering code to notify exposed individuals, and (3) getting information about the application (e.g. privacy).

We ran PLS path modelling using SmartPLS 3 (Ringle, Sarstedt, & Straub, 2012). PLS is apt for our purpose because it is a fully developed...
Table 4

| Dimens. | Consequence of COVID-19 | PTAs’ benefit for citizens | Code | Item |
|---------|-------------------------|----------------------------|------|------|
| PBs (adapted from Qazi et al. (2020)) | Limited eating and drinking outside | Being able to eat and drink outside | PB1 | I believe that using the PTA would enable me to eat and drink out more often. |
| PB4 | Limited travelling | Being able to travel | PB2 | I believe that using the PTA would enable me to use public transport more often. |
| SBs (new items) | Limited public health safety | Better public health safety | SB1 | I believe that, by using the PTA, I could help to protect critical groups from the pandemic. |
| PB5 | Limited crowd-gathering | Being allowed to gather in crowds | PB3 | I believe that using the PTA would enable me to go to crowded places more often. |
| PB4 | Limited outdoor activities | Being able to do activities outdoors | PB4 | I believe that using the PTA would enable me to go out for any activity more often. |
| SB5 | Limited general safety | Better general safety | SB6 | Overall, I feel that using the PTA would enable me to travel abroad more often. |

Table 5

| Factor 1, factor pattern coefficient (loading) | Factor 2, factor pattern coefficient (loading) | Communality | Uniqueness | Factor 1, factor structure coefficient (correlation) | Factor 2, structure coefficient (correlation) |
|---------------------------------------------|---------------------------------------------|--------------|------------|-----------------------------------------------|-----------------------------------------------|
| PB1 | -0.04 | 0.82 | 0.63 | 0.37 | 0.44 | 0.79 |
| PB2 | 0.04 | 0.76 | 0.61 | 0.39 | 0.49 | 0.78 |
| PB3 | -0.06 | 0.89 | 0.74 | 0.26 | 0.47 | 0.86 |
| PB4 | 0.01 | 0.88 | 0.79 | 0.21 | 0.53 | 0.89 |
| PB5 | 0.09 | 0.75 | 0.65 | 0.35 | 0.53 | 0.80 |
| SB1 | 0.78 | -0.02 | 0.60 | 0.40 | 0.77 | 0.44 |
| SB2 | 0.67 | 0.06 | 0.50 | 0.50 | 0.71 | 0.46 |
| SB3 | 0.75 | -0.02 | 0.55 | 0.45 | 0.74 | 0.43 |
| SB4 | 0.67 | 0.37 | 0.56 | 0.37 | 0.78 | 0.58 |
| SB5 | 0.84 | -0.13 | 0.59 | 0.41 | 0.76 | 0.36 |
| SB6 | 0.83 | 0.07 | 0.77 | 0.23 | 0.87 | 0.56 |

Table 6

| Conformatory factor analysis of PB and SB items, estimated using maximum likelihood; data set 2, n = 401. |
|---------------------------------------------|---------------------------------------------|--------------|------------|-----------------------------------------------|-----------------------------------------------|
| Factor1, loadings | Factor2, loadings | Communality | Uniqueness | Factor 1, factor structure coefficient (correlation) | Factor 2, structure coefficient (correlation) |
|---------------------|---------------------|-------------|------------|-----------------------------------------------|-----------------------------------------------|
| PB1 | 0.934 | 0.873 | 0.127 | 0.79 |
| PB2 | 0.921 | 0.848 | 0.152 | 0.78 |
| PB3 | 0.923 | 0.851 | 0.149 | 0.86 |
| PB4 | 0.907 | 0.822 | 0.178 | 0.89 |
| PB5 | 0.910 | 0.828 | 0.172 | 0.89 |
| SB1 | 0.885 | 0.783 | 0.217 | 0.80 |
| SB2 | 0.832 | 0.692 | 0.308 | 0.78 |
| SB3 | 0.907 | 0.823 | 0.177 | 0.86 |
| SB4 | 0.915 | 0.837 | 0.163 | 0.89 |
| SB5 | 0.893 | 0.705 | 0.295 | 0.87 |
| SB6 | 0.936 | 0.877 | 0.123 | 0.87 |

structural equation modelling approach suitable for explanatory research (Benitez, Henseler, Castillo, & Schuberth, 2020) that is widely used in information systems research (Chen, Wang, Nevo, Benitez, & Kou, 2017; Ringle et al., 2012). It is used to analyse complex models (Hair, Sarstedt, Ringle, & Mena, 2012), such as those with more than one mediation variables (Nitzl & Roldan, 2016). We ran a bootstrap analysis with 5000 subsamples to test the significance of the loadings and path coefficients (Chin, 1998; Hair, Hult, Ringle, & Sarstedt, 2017). In addition to the PLS algorithm, bootstrapping, and blindfolding calculations, we also performed MGA to determine whether the research model produces statistically different results based on the different collection times of the data used. At the time when responses included in data set 2 were collected, less information about COVID-19 existed. In addition, Slovenia, the country of data collection, was just coming out of its first lockdown, which had lasted approximately 2 months. However, when responses for data set 3 were collected, general knowledge had increased, and the second lockdown, which had lasted for approximately 4 months, was ending.

4.5.1. Assessment of the measurement model

According to Hair, Risher, Sarstedt, and Ringle (2019) we assessed item reliability, internal consistency reliability, convergent validity, and discriminant validity. In terms of item reliability, in the initial assessment, the loading for PCS1 item in data set 2 was too low (0.155), therefore, the item was removed from further analyses. Re-assessment of item reliability (Appendix B) confirmed item loadings of 0.7 or higher and significant (Hair et al., 2012; MacKenzie et al., 2011). The internal consistency reliability was validated using composite reliability (Hair, Ringle, & Sarstedt, 2012). A threshold value above 0.70 (Hair et al., 2017) was achieved for all items (Table 8). We also used Cronbach’s alpha as a more conservative measure for internal consistency reliability. All values were also higher than 0.7, thus suggesting satisfactory construct reliability (Hair et al., 2012). Also, convergent validity was evaluated using the average variance extracted (AVE). For each construct in both data sets (Table 8), AVE exceeded the recommended threshold of 0.5 (Hair et al., 2017).
PLS algorithm results: HTMT ratio of correlations for data group (Hair et al., 2017). The heterotrait–monotrait (HTMT) ratio assessments in both data sets indicate values below the threshold of 0.9, suggesting that discriminant validity in all data groups is acceptable (Henseler, Ringle, & Sarstedt, 2014).

### 4.5.2. Assessment of the structural model

We checked for collinearity issues by examining the variance-inflation factor (VIF) values of predictor constructs in the model (Hair et al., 2019). Since none of the VIF values in Table 8 exceeds the suggested limit of 5.0, collinearity among the predictor constructs is likely not a concern (Hair et al., 2017).

We evaluated in-sample predictive power with the measure $R^2$, and the out-of-sample prediction and in-sample explanatory power with the measure $Q^2$ (Hair et al., 2019). $R^2$ values range from 0 to 1, with higher values indicating greater explanatory power. To further explore effect sizes on ITU, we calculated $f^2$ values. Also, the blindfolding procedure (Chin, 1998; Henseler, Ringle, & Sarstedt, 2015) showed that $Q^2$ values for all dependent variables are above zero, indicating the predictive relevance for all the constructs (Hair et al., 2019). Table 12 depicts the $R^2$, $f^2$, and $Q^2$ values.

The statistical significance and relevance of the path coefficients is shown in Table 13. Since previous results suggested evidence for several potential mediating effects, we followed the procedures proposed by Hair et al. (2017) and performed a mediation analysis. The significance of the mediating effect of PBs (H2) and SBs (H3) were estimated. All three hypotheses were confirmed (Fig. 2). In the final step of the analysis, we examined whether the differences in path coefficients between the two sub-groups of data are significant. Table 15 presents MGA results.

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**Table 7**

| Construct | Acronym | ID | Indicator/item |
|-----------|---------|----|----------------|
| Intention to use PTA | ITU | ITU1 | Assuming I have access to the PTA, I intend to use it. |
| Perceived crisis severity | PCS | PCS1 | I care about the COVID-19 crisis. |
| Societal benefits of using PTA | SBs | SB1-6 | The COVID-19 crisis is meaningful to me. |

**Table 8**

PLS algorithm results: convergent validity, and internal consistency reliability.

| Construct | Data group | Convergent validity | Internal constancy reliability | Collinearity |
|-----------|------------|---------------------|------------------------------|--------------|
|            |            | AVE | CR | Cronbach’s Alpha | VIF |
| ITU        | 3 m.       | 0.941 | 0.985 | 0.979 | / |
|            | 12 m.      | 0.959 | 0.990 | 0.986 | / |
|            | All        | 0.954 | 0.988 | 0.984 | / |
| PCS        | 3 m.       | 0.627 | 0.893 | 0.853 | 1.153 |
|            | 12 m.      | 0.656 | 0.905 | 0.872 | 1.240 |
|            | All        | 0.647 | 0.901 | 0.866 | 1.204 |
| PBs        | 3 m.       | 0.875 | 0.972 | 0.964 | 2.709 |
|            | 12 m.      | 0.848 | 0.965 | 0.955 | 3.420 |
|            | All        | 0.856 | 0.967 | 0.958 | 3.104 |
| SBs        | 3 m.       | 0.880 | 0.969 | 0.962 | 3.673 |
|            | 12 m.      | 0.840 | 0.969 | 0.962 | 3.673 |
|            | All        | 0.833 | 0.968 | 0.960 | 3.285 |
| Age group  | 3 m.       | 1.000 | 1.000 | 1.000 | 1.010 |
|            | 12 m.      | 1.000 | 1.000 | 1.000 | 1.004 |
|            | All        | 1.000 | 1.000 | 1.000 | 1.001 |

**Table 9**

PLS algorithm results: HTMT ratio of correlations for data group “3 months” (data set 2).

| Construct | Age group | ITU | PBs | PCS | SB |
|-----------|-----------|-----|-----|-----|----|
| ITU       | 3 months  | 0.022 | 0.054 | 0.103 | 0.025 |
|            | 12 months | /     | 0.750 | 0.345 | 0.860 |
|            | All       | 0.691 | /     | 0.321 | 0.825 |
| PCS       | 3 months  | 0.089 | 0.042 | 0.133 | 0.169 |
|            | 12 months | 0.130 | 0.035 | 0.120 | 0.169 |
|            | All       | 0.691 | /     | 0.321 | 0.825 |
| SBs       | 3 months  | /     | 0.042 | 0.130 | 0.169 |
|            | 12 months | /     | 0.035 | 0.130 | 0.169 |
|            | All       | /     | 0.042 | 0.130 | 0.169 |

**Table 10**

PLS algorithm results: HTMT ratio of correlations for data group “12 months” (data set 3).

| Construct | Age group | ITU | PBs | PCS | SB |
|-----------|-----------|-----|-----|-----|----|
| ITU       | 0.145     | 0.028 | 0.758 | 0.090 | 0.049 |
| PBs       |           | 0.034 | 0.755 | 0.091 | 0.833 |
| PCS       |           | 0.011 | 0.364 | 0.091 | 0.838 |
| SBs       |           | 0.035 | 0.429 | 0.091 | 0.859 |

**Table 11**

PLS algorithm results: HTMT ratio of correlations for data group “all” (data set 2 and 3).

| Construct | Age group | ITU | PBs | PCS | SB |
|-----------|-----------|-----|-----|-----|----|
| ITU       | 0.112     | 0.034 | 0.755 | 0.091 | 0.049 |
| PBs       |           | 0.011 | 0.364 | 0.091 | 0.838 |
| PCS       |           | 0.012 | 0.364 | 0.091 | 0.859 |
| SBs       |           | 0.035 | 0.429 | 0.091 | 0.859 |

**Table 12**

PLS algorithm results for predictive validity ($R^2$), and $f^2$ effect size; and blindfolding results for predictive relevance ($Q^2$).

| Construct | Data group | $R^2$ | $f^2$ | $Q^2$ |
|-----------|------------|------|------|------|
| ITU       | 3 months   | 0.708 | /    | 0.660 |
|            | 12 months  | 0.690 | /    | 0.658 |
|            | All        | 0.691 | /    | 0.656 |
| PBs       | 3 months   | 0.089 | 0.042 | 0.077 |
|            | 12 months  | 0.133 | 0.035 | 0.112 |
|            | All        | 0.120 | 0.037 | 0.102 |
| SBs       | 3 months   | 0.130 | 0.057 | 0.106 |
|            | 12 months  | 0.193 | 0.321 | 0.160 |
|            | All        | 0.169 | 0.386 | 0.140 |
| PCS       | 3 months   | /     | 0.003 | /    |
|            | 12 months  | /     | 0.023 | /    |
|            | All        | /     | 0.018 | /    |
| Age group | 3 months   | /     | 1.010 | /    |
|            | 12 months  | /     | 1.004 | /    |
|            | All        | /     | 1.026 | /    |
5. Discussion

5.1. Discussion of the results

Our study investigated the impact of PCS, SBs and PBs on ITU. We collected data from 1201 respondents at two points in time: 3 months (data set 2) and 12 months (data set 3) of into the COVID-19 pandemic. We identified an initial list of the items for measuring PTAs’ benefits for citizens and established their content validity. The exploratory factor analysis results for data set 1 (Table 3) suggested two dimensions. Confirmatory factor analysis on data set 2 (Table 3) was used to replicate the two-dimensional structure. We tested the research model with PLS by using two data sets representing two COVID-19 situations.

PCS, SBs, and PBs alone explained 69.1% of the variance in ITU. The degree of variance explained is comparable to that of similar studies of intention to use PTAs. For example, Velicia-Martin et al. (2021) explained 76.9% of the variance and Hassandoust et al. (2020) explained 75%, while Sharma et al. (2020) explained 51%.

As a guideline, R² values higher than 0.25, 0.50, and 0.75 are considered weak, moderate, and substantial effect sizes (explanatory power), respectively (Hair, Ringle, & Sarstedt, 2011). The R² value 0.691 calculated for ITU (data group “all”, which merges data sets 2 and 3) indicates a moderate effect size, while the R² values for PBs (0.120) and SBs (0.169) do not reach the threshold for weak explanatory power. Furthermore, the Q² values higher than 0, 0.25, and 0.50 respectively indicate small, medium, and large predictive relevance of the PLS-path model (Hair et al., 2019). The results suggest a large predictive relevance for ITU (0.656) and a small one for PBs and SBs. Since predicting PBs and SBs was not the focus of our research, we are not concerned by their low R² and Q² values.

We further investigated which of the three constructs’ effect size—PCS, SBs, and PBs—was greatest for ITU. As a rule of thumb, values higher than 0.02, 0.15 and 0.35 respectively indicate small, medium and large f² effect sizes (Hair et al., 2019). We observed a large
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Table 14
MGA results: f² differences.

| Path         | Hypo. | f²-diff (f² for data sets 2 vs. 3) | t-test (3 months vs. 12 months) | p-value | Significance
|--------------|-------|-----------------------------------|---------------------------------|---------|---------------
| PBs → ITU    |       | -0.010                            | 0.136                           | 0.892   | NS            |
| PCS → ITU    | H1    | -0.064                            | 1.516                           | 0.130   | NS            |
| PCS → ITU    |       | -0.066                            | 1.265                           | 0.206   | NS            |
| PCS → SBs    |       | -0.079                            | 1.578                           | 0.115   | NS            |
| PBs → ITU    |       | 0.074                             | 0.984                           | 0.326   | NS            |
| PCS → ITU    | H2    | -0.016                            | 0.557                           | 0.577   | NS            |
| PCS → SBs    |       | -0.021                            | 0.463                           | 0.643   | NS            |
| Age group → ITU | | -0.105                            | 3.123                           | 0.002   | Sig.          |

**Table 15**
Path coefficients for the direct effect in different model settings (data group “all”, n = 1201).

| Direct effect | Direct relationship; a model with 2 constructs | Inclusion of PBs; a model with 3 constructs | Inclusion of SBs; a model with 3 constructs | Inclusion of PBs and SBs; a model with 4 constructs |
|---------------|-----------------------------------------------|-------------------------------------------|-------------------------------------------|--------------------------------------------------|
| PCS → ITU     | 0.407***                                      | 0.172***                                  | /                                         | 0.085***                                         |

*p = 0.000 (Sig.)

f² effect size on ITU in data group “all” with the construct SBs (0.386) while observing small effects with PBs (0.037) and age group (0.026). These results indicate that SBs play an important role in predicting ITU in our research model. On the other hand, the f² effect size in data group “all” for PCS is rather low (0.018). More specifically, in data set 2 the f² effect size value for PCS is 0.003, while in data set 3, the value is 0.023. Nine-month difference in time between the collections of the two data sets might explain the difference in the two f² effect sizes. When responses for data set 2 were collected, the COVID-19 pandemic had been ongoing in the country for 3 months, and the first lockdown was expected to end in a few days. Therefore, since the pandemic seemed to be coming to an end, and the virus was not presenting a threat to short-term plans for summer vacations, the effect size of PCS was 0.003. Nine months later, when responses for data set 3 were collected, the second lockdown, which was twice as long as the first one, was expected to end soon. Even though the data were collected just before the easing of the restrictions, the measured effect size in data set 3 (0.023) represents a small effect size. This is in line with crisis decision theory, which states that individuals assess PCS as higher when they believe that the crisis is likely to continue to be an issue in the future (Sweeney, 2008). People tend to re-assess severity when the crisis situation changes (Choi & Lin, 2009; Dionne et al., 2018). We conclude that over the period of 9 months, PCS gained importance in predicting intention to use PTAs and should not be overlooked in similar studies in the future.

The results for data group “all” support H1 (Table 13) and MGA analysis shows non-significant differences between the two data sets (Table 14); however, the level of support in the two data sets differs which warrants for a discussion. This again can be explained by the difference in times of data collection and the longer duration of COVID-19’s presence. The importance of PCS increased meaningfully over 9 months, resulting in significant impact on ITU. This behaviour is in line with crisis decision theory, which predicts that individuals consider the severity of the crisis when deciding whether to adopt the precautionary behaviour; however, individuals must perceive the crisis to be relatively severe for it to have a meaningful impact on decision making (Sweeney, 2008). Our findings are in line with De Zwart et al. (2010), who reported that perceptions about crisis severity and adoption of precautionary behaviours are significantly associated. However, Walrave et al. (2020) found no significant impact of PCS on ITU. We believe this finding was the result of the timing of their data collection, which took place in April 2020. Their findings are in line with our results from May 2020.

The results of data group “all” also depict support for H2 and H3 (Table 13) and MGA analysis show non-significant differences between the two data sets for both of the hypotheses (Table 14). A mediating effect exists when the indirect effect is significant (Nitzl & Roldan, 2016). Our results confirmed significance of the two indirect effects: PCS→PBs→ITU and PCS→SBs→ITU (Table 13). The t-tests for data group “all” indicate that all mediation effects via PBs and SBs are highly significant. Since both direct and indirect effects are significant, and all the effects point in positive direction, complementary partial mediation is suggested (Nitzl & Roldan, 2016). The mediation in our case suggests that a portion of the effect of PCS on ITU is mediated through PBs, whereas PCS still explains a portion of ITU that is independent of PBs. The same is true for SBs, where PCS still explains a portion of ITU that is independent of SBs. Table 15 shows how the direct effect changes after the inclusion of mediators (Nitzl & Hirsch, 2016). The inclusion of only PBs reduces the direct effect by 58%, while the inclusion of only SBs reduces it by 79%. When we include both PBs and SBs (without the...
structs: expected personal and expected community related outcomes of 
fits. Similarly, Sharma et al. (2020) studied two privacy calculus con 
detailed results for the impact of the two types of benefits. Walrave et al. 
However, we also showed the less powerful but still significant impact of 
if they appeal to citizens 
applications. According to Trang et al. (2020) , benefits are only effective 
would help to protect their well-being stimulates individuals to use such 
' 
individuals 
outcomes on people 
control variable), the initial direct effect is reduced by 80%. Thus we 
conclude that the mediating effect of SBS makes most of the difference. 
Lastly, we calculated the portion of the partial mediations (Nitzl & 
Roldan, 2016). The VAF value determines the extent to which the 
mediation process explains the dependent variable's variance. As a rule 
of thumb, values lower than 20%, between 20% and 80% and above 
80% depict zero mediation, partial mediation, and full mediation, 
respectively (Nitzl & Roldan, 2016). The results in Table 16 confirm 
partial mediation by both PBs and SBSs. 
The mediation results are in line with previous studies, which 
recognise the importance of individuals' belief in technology's benefits for 
adoption success (Davis et al., 1992; De Zwart et al., 2010; 
Velicia-Martin et al., 2021; Venkatesh et al., 2003). Davis et al. (1992) 
and Venkatesh et al. (2003) demonstrated that an individual’s intention 
to use technology is influenced mainly by their perceptions of how 
useful the technology is for improving their job performance. Similar to 
Cimperman et al. (2016), we shifted our focus from technologies that 
enhance job performance to those that improve health outcomes. PTAs 
constitute one such technology (Huang et al., 2020). We studied the 
direct and mediating impact of specific dimensions of PTA benefits for 
citizens by specifying two dimensions, namely personal and societal, in 
line with Trang et al. (2020). COVID-19 threatens both groups of ben 
efits, and PTA can help to protect them (Huang et al., 2020; Sweeney, 
2008). Our results are in line with Li et al. (2020), who found that indi 
viduals’ understanding that the use of mobile health applications 
would help to protect their well-being stimulates individuals to use such 
applications. According to Trang et al. (2020), benefits are only effective 
if they appeal to citizens’ altruistic and collective effort oriented con 
cerns. Our research confirms a substantial impact of societal benefits. 
However, we also showed the less powerful but still significant impact of 
personal benefits. 

Previous research by Hassandoust et al. (2021) verified that the 
direct impact of contact tracing benefits on intention to use PTA con 
sisted of societal and utilitarian benefits. However, they did not provide 
detailed results for the impact of the two types of benefits. Walrave et al. 
(2020) confirmed the impact of perceived personal and societal benefits 
on intention to use PTA. However, they did not follow established scale 
development guidelines to develop a scale for these two types of ben 
efits. Similarly, Sharma et al. (2020) studied two privacy calculus con 
structs: expected personal and expected community related outcomes of 
sharing information via PTA. They confirmed the direct impact of those 
outcomes on people’s attitudes. We differ from their research by 
focusing specifically on the outcomes related to COVID-19’s conse 
quences for citizens (Appendix A) and by reporting the results of personal 
and societal benefits’ direct and mediating impact on the intention 
to use PTA. 

Lastly, the results for data group “all” show a significant impact of 
control variable age group on ITU (Table 13) and MGA analysis shows 
significant differences between the two data sets (Table 14). For data set 
2, the impact of the age group on ITU is not significant, while for data set 
3, it is (Table 13). Increased knowledge (Sweeney, 2008) about 
COVID-19 in the critical groups may explain this difference. The older 
population may have been more inclined to adopt PTAs in latter data 
collection because they understood the crisis to be more self-relevant for 
them (Sweeney, 2008). Previous studies tested the impact of age groups 
organised as equal classes (e.g. from 18 to 24 years old) and found no 
significant impact (Walrave et al., 2020). However, we formulated the 
two age groups based on the characteristics of COVID-19, namely the 
increased mortality rate in older populations, and confirmed the 
importance of age. 

5.2. Implications for theory 

Our contribution to the information systems research community 
includes increased understanding of how to apply crises decision theory 
in adoption studies investigating technologies that are designed to help 
manage pandemic crises. We used the theory to discuss how perceptions 
of crisis severity are formed, and what influences the intention to use a 
particular precautionary behaviour – the use of PTAs. Previously the 
theory has been used to explain negative events where there was rela 
tively little time for an individual to decide about adopting a behaviour 
(Sayegh, Anthony, & Perrewé, 2004). However, in the case of COVID-19, 
individuals had more time to reason through the choices. Moreover, 
over time, knowledge about the pandemic crises changed, and the 
subsequent re-assessment of severity may have resulted in different 
impacts on PTA adoption. The long duration of the COVID-19 crisis 
made it possible to conduct a rigorous longitudinal study. We used the 
theory to investigate PTAs’ benefits for citizens and offer a scale to 
measure these benefits, namely, personal and societal, on the basis of 
COVID-19’s consequences for citizens. Our paper adds to Trang et al. 
(2020) a self-developed construct SBS and to Qazi et al. (2020) a 
rigorous empirical analysis of the reliability and validity of the construct 
PBs. 

Confirmation of our hypotheses confirms the importance of PCS for 
ITU, which was initially pinned down in Walrave et al. (2020), and 
demonstrates the mediating role of PBs and SBSs. We built on the study by 
Goodwin et al. (2011) with an empirical study of perceived crisis 
severity assessment at two points in time, after approximately 3 months 
and 12 months of COVID-19’s presence. We add to Trang et al. (2020) an 
empirical study on PTA’s benefits for both individuals and society. We 
found no statistically significant differences in the results of the three 
hypotheses, which demonstrates replicability of the hypotheses results; 
however, we found a statistically significant difference in the control 
variable age group. With this findings we contribute to PTA adoption 
research community (Hassandoust et al., 2021; Sharma et al., 2020; 
Velicia-Martin et al., 2021; Walrave et al., 2021). Finally, we contribute 
to the behaviour research community with an empirical study of adop 
tion of a precautionary behaviour during a pandemic crisis. 

5.3. Implications for practice 

Recurring waves of COVID-19 are having a lasting effect on society 
(Klein & Buis, 2020), and because the second wave of COVID-19 hit 
some countries even harder, digital contact tracing in Europe is evolving 
进一步 (Blasimme, Ferretti, & Vayena, 2021). Almost all Western 
countries have introduced voluntary PTAs for their citizens, but adop 
tion rates have been relatively low. It is crucial to understand more fully 
how policymakers and regulators can increase the use of voluntary PTAs 
(Klein & Buis, 2020) and hopefully achieve their mass acceptance 
(Trang et al., 2020). More specifically, a better understanding of pop 
ulations’ responses to COVID-19 can help optimise public health in 
terventions (Liao et al., 2011). Promotion of technology’s benefits 
positively influences intention to use technologies such as PTAs 
(Hanafizadeh et al., 2014). Consequently, our study focused on under 
standing how perceived crisis severity impacts citizens’ response to use 
PTA directly and indirectly via personal and societal benefits. 

An essential finding for practice is that our model with only three 
predicting constructs explains a surprisingly large part (69.1%) of the 
variance in intention to use. We acknowledge that these are not the only 
factors influencing the use of a technology in general or PTAs in 
particular. However, our results indicate that in such a crisis, focusing on 
a few core concepts can be sufficient to create significant changes in the 
public’s willingness to adopt new technologies. In line with Trang et al. 
(2020), we recommend that policymakers promote PTA use by 
communicating the benefits of PTAs, especially their benefits to society 

![Table 16](image-url)

| Path                  | VAF (%) |
|-----------------------|---------|
| PCS→PBs→ITU           | 44.61   |
| PCS→SBS→ITU           | 76.03   |

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These are useful findings for this and potential future crises.

Further, our study demonstrates the important effect of COVID-19’s perceived severity on willingness to use PTAs (Templeton et al., 2020). Our results show that intention to adopt the precautionary behaviour of using PTAs is affected by how severe individuals perceive the crisis to be, which is in line with crisis decision theory (Sweeney, 2008). Our findings may have wider practical applications, e.g. how to use such behavioural science findings to increase COVID-19 vaccine acceptance by designing individual-level interventions to convince end users to take vaccines. This could ensure satisfactory vaccination rates to safeguard society at large (Finney Rutten et al., 2021; Su et al., 2020; Volpp, Loewenstein, & Buxton, 2021).

5.4. Limitations and future work

The contexts of COVID-19 and PTAs are constantly evolving. In our study we distinguished between mandatory and voluntary PTAs, and we focused on voluntary PTAs for smartphones, which have very low penetration rates in most Western countries. Based on the context of our research (Welter & Gartner, 2016) we generalise our findings to societies which have or are planning to implement voluntary PTAs. Our research has several limitations related to the generalisability of our findings, which suggest new research opportunities. First, since different governments have implemented different restrictions, the set of benefits offered by PTAs may vary from country to country, and from time to time. As time passed, countries have experienced different COVID-19 consequences, at potentially different intensities. In future research, lists of SBs and PBs can be tailored according to the country of data collection. Second, we measured perceived crises severity when citizens were at the end of lockdowns. Future research could focus on measuring perceptions of severity at the beginning of lockdowns and evaluating their impact on willingness to adopt precautionary behaviours. Third, in our research model ITU is the predicted construct. However, actual adoption behaviour, user adherence to guidelines, policy integration, efficiency, and the needed features of the PTA (Colizza et al., 2021; Li et al., 2020; Weiβ, Esdar, & Hübner, 2021) should also be studied. Fourth, PTAs for smartphones are not the only mean to automatically trace proximities. In a recent opinion paper, He, Zhang, and Li (2021) discuss a set of different technologies through which, for instance, Internet-of-Things sensors could be installed. Future research should improve the understanding of citizens’ intention to use other devices. Fifth, our research focused on voluntary PTAs for smartphones while not acknowledging the applications’ technical characteristics, such as, for example, centralised vs. decentralised data storage (Barkley, 2020). Sixth, we used crisis decision theory to discuss only the positive consequences of using PTAs while omitting the negative ones, e.g., privacy concerns. Future research could apply crisis decision theory and extend our research model with, for example, constructs representing negative consequences of using PTA or add other positive consequences of PTA use.

Finally, common method bias may be an important problem since we used a single source of data. Indeed, one of the three data sets revealed a concern related to common method bias. According to Kock (2015), VIF values should be equal to or below 3.3; however, data set 3 has two values slightly higher than that. Nevertheless, when data sets 2 and 3 are merged into one (data set “all”), VIF values are all below 3.3. Consequently, we assume common method bias is not a major issue. Due to the fact that individuals are likely to re-assess COVID-19’s severity (Holmes, Henrich, Hancock, & Lestou, 2009; Sweeney, 2008), we needed to collect the data quickly to ensure that all respondents assessed the same COVID-19 situation. Therefore, we opted to hire a professional agency. The short 3-day time span of data collection for data sets 2 and 3 allowed our study to capture time-sensitive perceptions of crisis severity. We suggest future research to apply techniques for reducing common method bias, such as, different collection techniques, mixing items of different constructs, or using quasi-experimental research (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003).

6. Conclusion

Our study investigated the factors that influence the intention to use voluntary PTA. We used crisis decision theory as a lens to investigate the factors influencing the individuals’ decision to adopt such precautionary behaviour. We have performed three data collections to develop and validate our measurement scales and test the research hypotheses. Our findings suggest that citizens are more inclined to use voluntary PTAs as a precautionary behaviour if they have a higher perception of the crisis’ severity. Further, their perceived personal and societal benefits from using a PTA significantly mediate the relationship between crisis severity and intention to use a PTA. Our research provided new insights to information systems research by emphasising the importance of perceived crisis severity for the adoption of voluntary PTAs. The findings can help governments and other decision makers identify factors that should be considered in promoting self-precautionary behaviours and technology use during crises.

CRediT authorship contribution statement

Marina Trkman: Conceptualization, Methodology, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization, Project administration. Ales Popovic: Conceptualization, Methodology, Validation, Formal analysis, Writing – review & editing. Peter Trkman: Conceptualization, Methodology, Resources, Writing – review & editing, Supervision, Funding acquisition.

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Appendix A. COVID’s consequences for citizens

| Consequence                              | Description                                                                                           |
|------------------------------------------|-------------------------------------------------------------------------------------------------------|
| Limited eating and drinking outside      | Due to COVID-19, almost all countries have closed or limited the operation of restaurants (Gostin & Wiley, 2020). In-restaurant dining restrictions deleteriously affected the restaurant industry (Byrd et al., 2021). Consumers are more concerned about contracting COVID-19 from restaurant foods than food in general (Byrd et al., 2021). Research in mid-March 2020 indicated that 89% of respondents believed that food from grocery stores and home was safer than food from restaurants (Datassential, 2021). |
| Limited travelling                       | Rapid spread of the virus led governments to respond with travel restrictions (Studdert & Hall, 2020; Turcotte-Tremblay, Gali Gali, & Ridde, 2021). Public health travel restrictions are crucial measures to prevent transmission during commercial airline travel and mitigate cross-border importation and spread (Medley et al., 2021). Therefore, many air travel companies were banned from flying (Kalilbekken & Salen, 2021). More than a dozen countries have issued mandatory quarantine orders for travellers entering the state (Gostin & Wiley, 2020). Domestic travel restrictions have reduced the passenger volume up to 80% (Murano et al., 2021). |

(continued on next page)
Appendix B. Indicator and construct reliability

| Constr. | Indicator | Group of data | Indicator reliability | Construct’s reliability |
|---------|-----------|---------------|-----------------------|------------------------|
|         |           |               | Indicator loadings     | 2.5 - 97.5% CI         |
|         | ITU1      | 3 m.          | 0.971                 | 160.700                | [0.958 – 0.981]       |
|         |           | 12 m.         | 0.982                 | 483.685                | [0.978 – 0.986]       |
|         | ITU2      | 3 m.          | 0.968                 | 163.082                | [0.955 – 0.978]       |
|         |           | 12 m.         | 0.980                 | 286.649                | [0.972 – 0.986]       |
| ITU     | All       | 0.976         | 328.995               | 0.000                  | [0.970 – 0.982]       |
| ITU3    | 3 m.      | 0.971         | 205.799               | 0.000                  | [0.961 – 0.979]       |
|         | 12 m.     | 0.979         | 336.592               | 0.000                  | [0.973 – 0.985]       |
|         | All       | 0.977         | 399.959               | 0.000                  | [0.972 – 0.982]       |
| ITU4    | 3 m.      | 0.971         | 216.450               | 0.000                  | [0.961 – 0.979]       |
|         | 12 m.     | 0.977         | 352.647               | 0.000                  | [0.971 – 0.982]       |
|         | All       | 0.975         | 410.481               | 0.000                  | [0.970 – 0.980]       |
| PCS2    | 3 m.      | 0.781         | 28.592                | 0.000                  | [0.724 – 0.831]       |
|         | 12 m.     | 0.847         | 75.600                | 0.000                  | [0.824 – 0.886]       |
|         | All       | 0.825         | 75.600                | 0.000                  | [0.804 – 0.846]       |
| PCS3    | 3 m.      | 0.742         | 20.176                | 0.000                  | [0.659 – 0.804]       |
|         | 12 m.     | 0.745         | 31.715                | 0.000                  | [0.695 – 0.787]       |
|         | All       | 0.746         | 38.520                | 0.000                  | [0.706 – 0.781]       |
| PCS4    | 3 m.      | 0.837         | 36.688                | 0.000                  | [0.785 – 0.875]       |
|         | 12 m.     | 0.849         | 58.814                | 0.000                  | [0.818 – 0.874]       |
|         | All       | 0.845         | 69.741                | 0.000                  | [0.819 – 0.867]       |
| PCS5    | 3 m.      | 0.752         | 20.120                | 0.000                  | [0.665 – 0.813]       |
|         | 12 m.     | 0.738         | 27.910                | 0.000                  | [0.683 – 0.784]       |
|         | All       | 0.743         | 35.104                | 0.000                  | [0.696 – 0.790]       |
| PCS6    | 3 m.      | 0.840         | 35.182                | 0.000                  | [0.786 – 0.880]       |
|         | 12 m.     | 0.861         | 74.461                | 0.000                  | [0.836 – 0.882]       |
|         | All       | 0.855         | 80.852                | 0.000                  | [0.833 – 0.875]       |
| PB1     | 3 m.      | 0.946         | 113.601               | 0.000                  | [0.929 – 0.961]       |
|         | 12 m.     | 0.935         | 177.220               | 0.000                  | [0.921 – 0.947]       |
| PB2     | 3 m.      | 0.938         | 110.370               | 0.000                  | [0.921 – 0.953]       |
|         | 12 m.     | 0.919         | 115.351               | 0.000                  | [0.903 – 0.934]       |
| Constr. | Indicator | Group of data | Indicator reliability | Indicator loadings | t-test | p-value | Construct's reliability |
|---------|-----------|---------------|-----------------------|-------------------|--------|---------|------------------------|
| PB3     | All       | 0.925         | 151.811               | 0.000             | [0.913 – 0.937] |
| PB3     | 3 m.      | 0.938         | 104.669               | 0.000             | [0.919 – 0.953] |
| PB4     | 12 m.     | 0.926         | 130.613               | 0.000             | [0.912 – 0.939] |
| PB4     | All       | 0.930         | 161.025               | 0.000             | [0.918 – 0.940] |
| PB4     | 3 m.      | 0.927         | 91.960                | 0.000             | [0.905 – 0.945] |
| PB4     | 12 m.     | 0.888         | 74.015                | 0.000             | [0.863 – 0.910] |
| PB5     | All       | 0.900         | 100.414               | 0.000             | [0.881 – 0.916] |
| PB5     | 3 m.      | 0.929         | 103.668               | 0.000             | [0.911 – 0.946] |
| SB1     | All       | 0.933         | 189.520               | 0.000             | [0.923 – 0.942] |
| SB1     | 3 m.      | 0.909         | 78.392                | 0.000             | [0.884 – 0.929] |
| SB2     | All       | 0.921         | 158.423               | 0.000             | [0.916 – 0.941] |
| SB2     | 3 m.      | 0.855         | 49.624                | 0.000             | [0.866 – 0.902] |
| SB2     | 12 m.     | 0.885         | 95.206                | 0.000             | [0.866 – 0.902] |
| SB3     | All       | 0.875         | 104.125               | 0.000             | [0.858 – 0.891] |
| SB3     | 3 m.      | 0.922         | 100.014               | 0.000             | [0.902 – 0.938] |
| SB4     | All       | 0.933         | 203.919               | 0.000             | [0.924 – 0.943] |
| SB4     | 3 m.      | 0.928         | 104.646               | 0.000             | [0.909 – 0.943] |
| SB5     | All       | 0.917         | 101.636               | 0.000             | [0.894 – 0.929] |
| SB5     | 3 m.      | 0.878         | 93.760                | 0.000             | [0.893 – 0.930] |
| SB6     | All       | 0.888         | 116.361               | 0.000             | [0.874 – 0.909] |
| SB6     | 3 m.      | 0.940         | 134.891               | 0.000             | [0.926 – 0.953] |
| SB6     | 12 m.     | 0.940         | 171.336               | 0.000             | [0.928 – 0.950] |
| SBs     | All       | 0.939         | 215.402               | 0.000             | [0.930 – 0.947] |

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