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.

Keywords: COVID-19, crisis severity, tracing applications, benefits, intention to use

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 (Beaunoyer et al., 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 et al., 2020; Riemer et al., 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 (Laukkanen, 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 (Kanbach 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 et al., 2018). Although there are many studies in the area of e-health adoption (Cimperman et al., 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 et al., 1999; Venkatesh & Davis, 2000), PTA adoption is a novel situation, and further research on influencing constructs is needed (Laukkanen, 2019; Pan & Zhang, 2020; Shiau et al., 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 et al., 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 organized 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 theorizes 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 negative consequences of a crisis (Quinn et al., 2009). In addition, behaviour plays a major role in the spread of infectious diseases such as COVID-19 (Funk et al., 2010). In the following two subsections, we use crisis decision theory to better understand how perceived crisis severity develops and what predicts the adoption of precautionary behaviour.

2.1.1 Perceived crisis severity

In assessing crisis severity, people attempt to understand the crisis they are facing (Sweeney, 2008). Zhou et al. (2019) define perceived crisis severity as the degree to which individuals assess a crisis to be intense. Perceived crisis severity is assessed from the perspective of the individual and may not correspond to the actual risk (Coelho & Codeco, 2009). The severity assessment is sensitive to the individual's understanding of the crisis and the set of emotions accompanying that understanding (Brewer et al., 2004; Goodwin et al., 2011; Lee, 2016; Sweeney, 2008; Zhou et al., 2019), both of which may vary over time (Ibuka et al., 2010; Sweeney, 2008). Dangerous and life-threatening situations activate negative emotions such as worry, anger, regret, guilt, fear, disappointment, and shame (Dionne et al., 2018; Liao et al., 2011). Individuals seek to understand who is affected by the crisis by assessing the consequences of the crisis on their own lives (Sweeney, 2008; Zhou et al., 2019) and using logic to evaluate the threat (Ibuka et al., 2010; Zhou et al., 2019). They also assess information about the consequences of the disease on non-health-related life domains and consider information about the severity of protective measures and lockdown conditions (Lieberoth et al., 2021). Individuals' understanding of the situation created by the crisis is an important contributor to the success of containment strategies during an infectious disease outbreak (Wong & Sam, 2011). According to crisis decision theory, the degree of perceived crisis severity corresponds to the number of consequences, assessed self-relevance, and the likelihood that the crisis will continue to be an issue in the future (Sweeney, 2008).

COVID-19 is an ideal example of a crisis with a large number of consequences as it brought about the enactment of multiple restrictions to minimize citizens' proximity to one another (Beaunoyer et al., 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 et al., 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 (Salathé 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).

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
		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 1: The role of crisis decision theory in individuals' assessments of possible responses to a precautionary behaviour

East Asia is a notable example of how mandatory use of PTAs can slow COVID-19 down (Huang et al., 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) 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 rigor 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 (Grekousis, 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 et al., 2020a).

	(Sharma, S. et al., 2020)	**(Velicia-Martin et al., 2021)**	**(Hassandoust et al., 2021)**	**(Walrave et al., 2020b)**	**Our study**
Perceived severity in context of COVID-19	No	No	No	No	Yes
Benefits of PTA	No	No	Yes	No	Yes
(Behaviour) intention to use PTA	Yes	Yes	Yes	Yes	Yes
Number of all constructs in the research model (without control variables)	13	7	13	8	4
Theory/model used	procedural fairness theory, dual calculus theory, protection motivation theory, theory of planned behavior, and Hofstede's cultural dimension theory	Technology acceptance model	privacy calculus theory	Extended unified theory of acceptance and use of technology model	Crises decision theory
Respondents	714	482	856	1500	1201
Country of the respondents	Fiji	United Kingdom	United States	Belgium	Slovenia
Analyses	SEM	SEM-MGA	SEM	SEM	SEM-MGA

SEM=structural equation modeling; MGA=multigroup analyses

Table 2: Similar studies on PTA adoption

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 et al., 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 et al., 1992). Over the years, several studies have identified perceived usefulness as a large predictor of intention to use a technology (Bitler et al., 2020; Hanafizadeh et al., 2014; Venkatesh & Davis, 2000; Venkatesh & Morris, 2000). 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 et al., 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 minimizing new infections and individual health performance by minimizing 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 & Busis (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 drink 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, emphasising the severity of COVID-19 (Ting et al., 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 be more inclined to respond by adopting a PTA (Sweeney, 2008; Walrave et al., 2020a). 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 et al., 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 et al., 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 et al., 2010; Sweeney, 2008). Similar to ways mobile health applications can allow patients to satisfy their health care needs (Li et al., 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 et al., 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 (Brewer et al., 2004; De Zwart et al., 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 socialization (less alienation) and better performance of national economies. PTA use is strongly shaped by citizens' beliefs (Brewer 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., 2020a).

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 et al., 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 et al., 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 Figure 1.

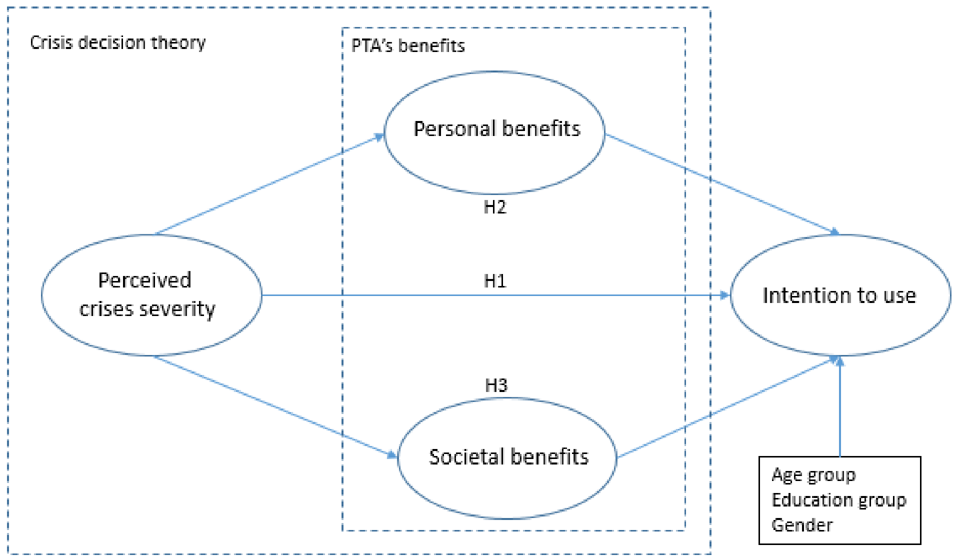


Figure 1: Research model

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.

	Data set 1	Data set 2 (group of data ’3 months’)	Data set 3 (group of data ’12 months’)
Respondents	International students at University of Ljubljana n=182	Residents of Slovenia n=401	Residents of Slovenia n=800
Chronological time of data collection	From 11^{th} until 19^{th} of May 2020	From 27^{th} until 29^{th} of May 2020	From 8^{th} until 10^{th} of March 2021
Time in relation to COVID-19’s lockdown in Slovenia	The number of new infections is decreasing.	The end of first lockdown which lasted app. 2 months.	The end of second lockdown which lasted app. 4 months.
Who collected data?	The authors of the paper	Professional agency	Professional agency
Age (in years)	age <=24; n=182	18-24; n=51 25-34; n=64 35-44; n=75 45-54; n=69 55-64; n=84 65-74; n=58	18-24; n=116 25-34; n=115 35-44; n=99 45-54; n=99 55-64; n = 185 65-74; n = 188
Gender	male = 114 female = 68	male = 213 female = 188	male = 425 female =375
Achieved education level	Primary school: n = 0 Secondary school: n = 182 Bachelor’s degree: n = 0 Master’s degree: n = 0 Doctoral degree: n = 0	Primary school : n = 9 Secondary school: n = 169 Bachelor’s degree: n = 184 Master’s degree: n = 37 Doctoral degree: n = 2	Primary school: n = 24 Secondary school: n = 376 Bachelor’s degree: n = 316 Master’s degree: n = 72 Doctoral degree: n = 12
PTA installed	(not applicable)	(not applicable)	Yes =300; No = 500
Analysis	**Exploratory factor analyses** (items in Table 4)	**Confirmatory factor analysis** (items in Table 4) **PLS-MGA** (items in Table 7)	**PLS-MGA** (items in Table 7)

Table 3: Characteristics of the three data sets

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 et al., 2011; Mimouni-Chaabane & Volle, 2010; Motamarri et al., 2020). Based on the literature review (summarized 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. Ds 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).

Dimens.	Consequence of COVID-19	PTAs’ benefit for citizens	Code	Item
PBs (adapted from Qazi, 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.
	Limited travelling	Being able to travel	PB2	I believe that using the PTA would enable me to use public transport more often.
			PB5	I believe that using the PTA would enable me to travel abroad more often.
	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.
	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.
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.
			SB3	I believe that, by using the PTA, there would be less infected citizens.
			SB5	I believe that, by using the PTA, I could help health authorities trace paths of infection.
	Limited performance of national economy	Better performance of national economy	SB2	I believe that, by using the PTA, I could help the national economy to re restart.
	Alienation	Less alienation	SB4	I believe that using the PTA may allow for an easing of the social distancing requirements.
	Limited general safety	Better general safety	SB6	Overall, I feel that using the PTA within a community would increase the safety of all.

Table 4: Items used in exploratory and confirmatory factor analysis

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.

	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**	0.18	0.63	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 5: Exploratory factor analysis of PTAs' benefits for citizens items, estimated using iterated principal axis factoring with an oblique rotation; data set 1, n=182

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, 2006).

	Factor1, loadings	Factor2, loadings	Communality	Uniqueness
PB1		0.934	0.873	0.127
PB2		0.921	0.848	0.152
PB3		0.923	0.851	0.149
PB4		0.907	0.822	0.178
PB5		0.910	0.828	0.172
SB1	0.885		0.783	0.217
SB2	0.832		0.692	0.308
SB3	0.907		0.823	0.177
SB4	0.915		0.837	0.163
SB5	0.839		0.705	0.295
SB6	0.936		0.877	0.123

Table 6: Confirmatory factor analysis of PB and SB items, estimated using maximum likelihood; data set 2, n=401

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 et al. (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 to 54 and the other with respondents aged 55 to 74.

We selected Slovenia as a country that is representative of Western society. Slovenia has approximately two million citizens. The government developed its own decentralized 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, 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).

Construct	*Acronym*	*ID*	*Indicator/item*
Intention to use PTA (Alalwan et al., 2017; Venkatesh et al., 2017)	ITU	ITU1	Assuming I have access to the PTA, I intend to use it.
		ITU2	Given that I have access to the PTA, I predict that I would use it.
		ITU3	I predict I would use the PTA on a regular basis if I had access to it.
		ITU4	I intend to use the PTA in the future.
Perceived crisis severity (Zhou et al., 2019)	PCS	PCS1	I care about the COVID-19 crisis.
		PCS2	Further news about the COVID-19 crisis interests me.
		PCS3	I feel quite anxious about the COVID-19 crisis.
		PCS4	I am worried about the COVID-19 crisis.
		PCS5	I feel influenced by this crisis.
		PCS6	The COVID-19 crisis is meaningful to me.
Personal benefits of using PTA, adapted from (Qazi et al., 2020)	PBs	PB1-4	(Refer to Table 4.)
Societal benefits of using PTA (Self-developed)	SBs	SB1-6	(Refer to Table 4.)

Table 7: Questionnaire items

We ran PLS path modelling using SmartPLS 3 (Ringle et al., 2012). PLS is apt for our purpose because it is a fully developed structural equation modelling approach suitable for explanatory research (Benitez et al., 2020) that is widely used in information systems research (Chen, Y. et al., 2017; Ringle et al., 2012). It is used to analyse complex models (Hair et al., 2012), such as those with more than one mediation variables (Nitzl et al., 2016). We ran a bootstrap analysis with 5,000 subsamples to test the significance of the loadings and path coefficients (Chin, 1998; Hair et al., 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 two months. However, when responses for data set 3 were collected, general knowledge had increased, and the second lockdown, which had lasted for approximately four months, was ending.

4.5.1 Assessment of the measurement model

According to Hair et al. (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 (CR). 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).

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.	0.820	0.965	0.956	2.823
	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 8: PLS algorithm results: convergent validity, and internal consistency reliability

Tables 9-11 show the assessment of discriminant validity (Hair et al., 2019). 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 et al., 2014).

Construct	*Age group*	*ITU*	*PBs*	*PCS*	*SB*
Age group					
ITU	0.022				
PBs	0.054	0.750			
PCS	0.103	0.345	0.321		
SBs	0.025	0.860	0.825	0.389	

Table 9: PLS algorithm results: HTMT ratio of correlations for data group "3 months" (data set 2)

Construct	*Age group*	*ITU*	*PBs*	*PCS*	*SB*
Age group					
ITU	0.145				
PBs	0.028	0.758			
PCS	0.090	0.442	0.378		
SBs	0.049	0.833	0.878	0.452	

Table 10: PLS algorithm results: HTMT ratio of correlations for data group "12 months" (data set 3)

Construct	*Age group*	*ITU*	*PBs*	*PCS*	*SB*
Age group					
ITU	0.112				
PBs	0.034	0.755			
PCS	0.091	0.416	0.364		
SBs	0.035	0.838	0.859	0.429	

Table 11: PLS algorithm results: HTMT ratio of correlations for data group "all" (data set 2 and 3)

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 et al., 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.

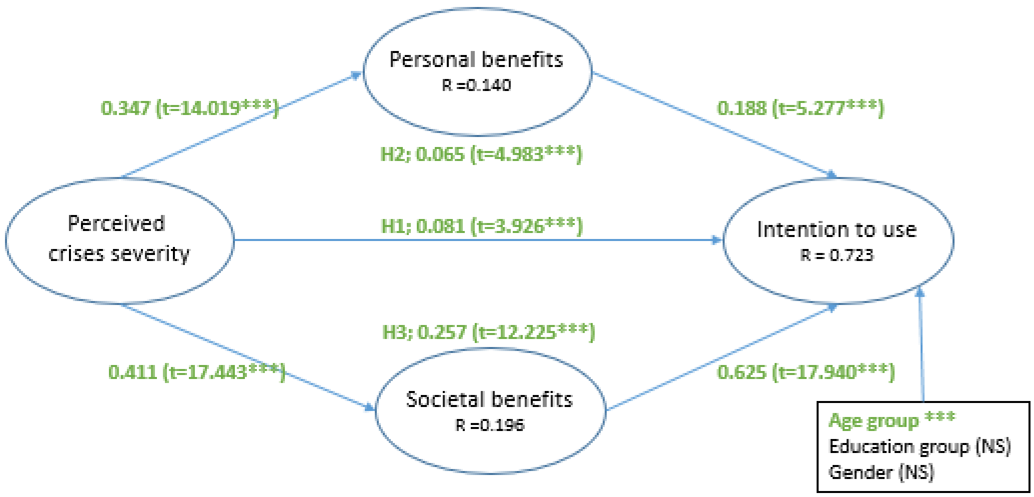
The statistical significance and relevance of the path coefficients is shown in Table 13. Since previous results suggested evidence for several potential mediating effects, we followed the procedures proposed by Hair et al. (2017) and performed a mediation analysis. The significance of the mediating effect of PBs (H2) and SBs (H3) were estimated. All three hypotheses were confirmed (Figure 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.

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	0.557	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	/

Table 12: PLS algorithm results for predictive validity (R^2), and f^2 effect size; and blindfolding results for predictive relevance (Q^2).

Path	***Hypo.***	***Data group***	***Path Coefficient***	***SD***	***t-test***	***p-value***	***Significance ($p< 0.05$)***	***2.5% - 97.5% CI bias corrected***
PCS → PBs		3 months	0.299	0.043	6.880	0.000	Sig.	[0.208 – 0.379]
		12 months	0.365	0.029	12.550	0.000	Sig.	[0.308 – 0.421]
		All	0.347	0.025	14.019	0.000	Sig.	[0.296 – 0.395]
PBs → ITU		3 months	0.182	0.055	3.335	0.001	Sig.	[0.075 – 0.287]
		12 months	0.192	0.047	4.144	0.000	Sig.	[0.106 – 0.291]
		All	0.188	0.036	5.277	0.000	Sig.	[0.018 – 0.260]
PCS → ITU	H1	3 months	0.030	0.033	0.915	0.360	Non-sig.	[-0.035 – 0.094]
		12 months	0.095	0.026	3.709	0.000	Sig.	[0.045 – 0.145]
		All	0.081	0.021	3.926	0.000	Sig.	[0.041 – 0.121]
PCS → PBs → ITU	H2	3 months	0.054	0.018	2.957	0.003	Sig.	[0.021 – 0.093]
		12 months	0.070	0.018	3.936	0.000	Sig.	[0.039 – 0.109]
		All	0.065	0.013	4.983	0.000	Sig.	[0.041 – 0.092]
PCS → SBs		3 months	0.360	0.044	8.268	0.000	Sig.	[0.270 – 0.439]
		12 months	0.439	0.027	16.105	0.000	Sig.	[0.383 – 0.489]
		All	0.411	0.024	17.443	0.000	Sig.	[0.363 – 0.455]
SBs → ITU		3 months	0.678	0.051	13.297	0.000	Sig.	[0.577 – 0.772]
		12 months	0.604	0.047	12.876	0.000	Sig.	[0.506 – 0.690]
		All	0.625	0.035	17.940	0.000	Sig.	[0.555 – 0.693]
PCS → SBs → ITU	H3	3 months	0.244	0.036	6.732	0.000	Sig.	[0.175 – 0.316]
		12 months	0.265	0.027	9.761	0.000	Sig.	[0.212 – 0.319]
		All	0.257	0 021	12.255	0.000	Sig.	[0.216 – 0.298]
Age group → ITU		3 months	0.012	0.027	0.445	0.657	Non-sig.	[-0.039 – 0.062]
		12 months	0.017	0.020	5.889	0.000	Sig.	[0.078 – 0.155]
		All	0.090	0.016	5.563	0.000	Sig.	[0.058 – 0.122]

Table 13: Bootstrapping results: path coefficient, standard deviation (SD), t-test results and confidence intervals (CI) with bias corrected



***Sig. p<000; ** Sig. p<0.001; *Sig. p<0.05; NS=non-sig.

Figure 2: Summary of PLS analysis results (group of data=All; n=1201)

Path	***Hypo.***	***f^2-diff (|3 months – 12 months|)***	***t-test (3 months vs. 12 months)***	***p-value***	***Significance (p< 0.05)***
PBs → ITU		-0.010	0.136	0.892	NS
PCS → ITU	H1	-0.064	1.516	0.130	NS
PCS → PBs		-0.066	1.265	0.206	NS
PCS → SBs		-0.079	1.578	0.115	NS
SBs → ITU		0.074	0.984	0.326	NS
PCS→PBs→ITU	H2	-0.016	0.557	0.577	NS
PCS→SBs→ITU	H3	-0.021	0.463	0.643	NS
Age group→ITU		-0.105	3.123	0.002	Sig.

Table 14: MGA results: f2 differences.

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 (2021) explained 75%, while Sharma et al. (2020) explained 51%.

As a guideline, R^2 values higher than 0.25, 0.50, and 0.75 are considered weak, moderate, and substantial effect sizes (explanatory power), respectively (Hair et al., 2011). The R^2 value 0.691 calculated for ITU (data group "all", which merges data sets 2 and 3) indicates a moderate effect size, while the R^2 values for PBs (0.120) and SBs (0.169) do not reach the threshold for weak explanatory power. Furthermore, the Q^2 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 R^2 and Q^2 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 f^2 effect sizes (Hair et al., 2019). We observed a large f^2 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 f^2 effect size in data group "all" for PCS is rather low (0.018). More specifically, in data set 2 the f^2 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 f^2 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 nine 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 nine 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. (2020a) 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 et al., 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 et al., 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 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 et al., 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 et al., 2016). The results in Table 16 confirm partial mediation by both PBs and SBs.

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***	/	0.083***
		/	0.085***	

Table 15: Path coefficients for the direct effect in different model settings (data group "all", n=1201)

Path	VAF (%)
PCS→PBs→ITU	44.61
PCS→SBs→ITU	76.03

Table 16: Mediation test (data group "all", n=1201)

The mediation results are in line with previous studies, which recognize the importance of individuals' belief in technology's benefits for adoption success (Velicia-Martin et al., 2021; De Zwart et al., 2010; Venkatesh et al., 2003; Davis et al., 1992). 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 benefits, and PTA can help to protect them (Sweeney, 2008; Huang et al., 2020). Our results are in line with Li et al. (2020), who found that individuals' 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 concerns. 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 consisted of societal and utilitarian benefits. However, they did not provide detailed results for the impact of the two types of benefits. Walrave et al. (2020a) 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 benefits. Similarly, Sharma et al. (2020) studied two privacy calculus constructs: 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 consequences 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 organized as equal classes (e.g. from 18 to 24 years old) and found no significant impact (Walrave et al., 2020a). 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 relatively little time for an individual to decide about adopting a behaviour (Sayegh et al., 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 (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. (2020a), and demonstrates the mediating role of PBs and SBs. We built on the study by Goodwin (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, S. et al., 2020; Velicia-Martin et al., 2021; Walrave et al., 2020b). Finally, we contribute to the behaviour research community with an empirical study of adoption 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, & Busis, 2020), and because the second wave of COVID-19 hit some countries even harder, digital contact tracing in Europe is evolving further (Blasimme et al., 2021). Almost all Western countries have introduced voluntary PTAs for their citizens, but adoption rates have been relatively low. It is crucial to understand more fully how policymakers and regulators can increase the use of voluntary PTAs (Klein, & Busis, 2020) and hopefully achieve their mass acceptance (Trang et al., 2020). More specifically, a better understanding of populations' responses to COVID-19 can help optimize public health interventions (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 understanding 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 (Van Bavel et al., 2020). 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 et al., 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 generalize our findings to societies which have or are planning to implement voluntary PTAs. Our research has several limitations related to the generalizability 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; Weiß et al., 2021) should also be studied. Fourth, PTAs for smartphones are not the only mean to automatically trace proximities. In a recent opinion paper, He et al. (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, centralized vs. decentralized 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 et al., 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 three-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 et al., 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 emphasizing 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. **Aleš Popovič:** 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 et al., 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 (Kallbekken & Sælen, 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).
Limited outdoor activities	During a public health emergency such as the COVID-19 pandemic, the use of outdoor recreation spaces by large numbers of people may also increase the risk of community spread (NCCEH, 2021). Governments advised the population to stay home and limit outdoor physical activity such as walking or jogging (KFF, 2021). Outdoor education programs have been cancelled (Quay et al., 2020). The restrictions can affect recreation visitation behaviour in the long run (Landry et al., 2020).
Limited crowd-gathering	COVID-19 mitigation measures decrease the civil rights related to freedom of crowd-gathering (Turcotte-Tremblay et al., 2021). Bans and fines for gathering were introduced by governments to balance disease control and civil liberties (Studdert & Hall, 2020). Governments have tightened restrictions from initial bans on groups of 1000, later bans on groups from 250, to 50, to 10, and eventual bans on groups of any size (Gostin & Wiley, 2020). The bans affect religious congregations, entertainment, business meetings, and even political rallies (Gostin & Wiley, 2020). Some governments have imposed night-time curfews to limit the gatherings (Gostin & Wiley, 2020).
Limited public health safety	The rapid spread of the disease endangers the health safety of all. However, the older population seems to be most threatened (Jansen-Kosterink et al., 2020; Rowe, 2020). Next, people with poor self-rated health were observed to be associated with greater levels of stress, anxiety, and depression, loneliness, worry and guilt (Barnes, 2020; Van Bavel et al., 2020; Wang et

	al., 2020), which negatively affect their physical well-being (Haghani et al., 2020; Lieberoth et al., 2021; Salari et al., 2020). Moreover, the long-term presence of the virus has disrupted the performance of other health and medical services (Bavli et al., 2020; UNDP, 2020; WHO, 2020).
Limited general safety	COVID-19's restrictions threaten general safety, such as social safety, food safety, domestic safety, cyber safety, economic safety and supply-chain safety (Haghani et al., 2020; Jansen-Kosterink et al., 2020). This fear and uncertainty have the potential to result in an environment that generates diverse forms of violence (Usher et al., 2020), including intimate-partner violence and homicides (Boman & Gallupe, 2020). COVID-19 can impact the mental health of people in different, often disadvantaged communities, and it results in a number of psychological disorders (Salari et al., 2020). It has a disproportionately large impact on low-income families, with school and child-care centres no longer providing free- and reduced-price school meals (Bitler et al., 2020). COVID-19's consequences can severely decrease general safety in society (Templeton et al., 2020).
Alienation	Countries tend to prevent new infections with social distancing strategies such as lockdowns (Pan et al., 2020). Due to social distancing requirements, many employees are requested to work from home (Vyas & Butakhieo, 2020), and many children are being schooled from home (Turcotte-Tremblay et al., 2021). During extended school closures, educational development is disrupted (Gostin & Wiley, 2020). Alienation raises profound questions of culture, faith, and family (Gostin & Wiley, 2020). Because of the alienation, many people suffer from open prison effects (Rowe et al., 2020; Templeton et al., 2020; Van Bavel et al., 2020).
Limited performance of the national economy	COVID-19's restrictions threaten the national economy's regular performance. Due to distancing requirements, losses of business activity have been felt across many industries (Fairlie, 2020). Business closures cause unemployment and economic harm (Gostin & Wiley, 2020). The COVID-19 pandemic has created an enormous shock of uncertainty, comparable to the one created by the Great Depression in the period from 1929 until 1933 (Baker et al., 2020). In the United States of America, 43% of small businesses have been closed temporarily, and employment has fallen by 40% (Bartik et al., 2020). Furthermore, the virus has disrupted many businesses across the European Union, resulting in an immense drag on revenues and cash flows (Mirza et al., 2020). Many industries worldwide are faced with a partial or complete decrease in business activity. For example, the lockdown led to a 98% fall in international tourist numbers in May 2020 compared with May 2019 (UNWTO, 2020).

Appendix B: Indicator and construct reliability

Constr.	Indicator	Group of data	*Indicator reliability* *Indicator loadings*	*t-test*	*p-value*	*Construct's reliability* *2.5% - 97.5% CI*
ITU	ITU1	3 m.	0.971	160.700	0.000	[0.958 – 0.981]
		12 m.	0.982	483.685	0.000	[0.978 – 0.986]
		All	0.979	448.868	0.000	[0.974 – 0.983]
	ITU2	3 m.	0.968	163.082	0.000	[0.955 – 0.978]
		12 m.	0.980	286.649	0.000	[0.972 – 0.986]
		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]
PCS	PCS2	3 m.	0.781	28.592	0.000	[0.724 – 0.831]
		12 m.	0.847	75.609	0.000	[0.824 – 0.868]
		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	[0.698 – 0.780]
	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]
PBs	PB1	3 m.	0.946	113.601	0.000	[0.929 – 0.961]
		12 m.	0.935	139.422	0.000	[0.921 – 0.947]
		All	0.938	178.207	0.000	[0.927 – 0.948]
	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]
		All	0.925	151.811	0.000	[0.913 – 0.937]
	PB3	3 m.	0.938	104.669	0.000	[0.919 – 0.953]
		12 m.	0.926	130.613	0.000	[0.912 – 0.939]
		All	0.930	161.025	0.000	[0.918 – 0.940]
	PB4	3 m.	0.927	91.960	0.000	[0.905 – 0.945]
		12 m.	0.888	74.015	0.000	[0.863 – 0.910]
		All	0.900	100.414	0.000	[0.881 – 0.916]
	PB5	3 m.	0.929	103.663	0.000	[0.911 – 0.946]
		12 m.	0.935	161.686	0.000	[0.923 – 0.946]
		All	0.933	189.520	0.000	[0.923 – 0.942]
SBs	SB1	3 m.	0.909	78.392	0.000	[0.884 – 0.929]
		12 m.	0.930	142.870	0.000	[0.916 – 0.941]
		All	0.921	158.423	0.000	[0.911 – 0.933]
	SB2	3 m.	0.855	49.624	0.000	[0.866 – 0.902]
		12 m.	0.885	95.206	0.000	[0.866 – 0.902]
		All	0.875	104.125	0.000	[0.858 – 0.891]
	SB3	3 m.	0.922	100.014	0.000	[0.902 – 0.938]
		12 m.	0.938	180.797	0.000	[0.928 – 0.948]
		All	0.933	203.919	0.000	[0.924 – 0.942]
	SB4	3 m.	0.928	104.646	0.000	[0.909 – 0.943]
		12 m.	0.913	101.636	0.000	[0.894 – 0.929]
		All	0.917	135.760	0.000	[0.903 – 0.930]
	SB5	3 m.	0.878	59.538	0.000	[0.847 – 0.905]
		12 m.	0.892	98.582	0.000	[0.874 – 0.909]
		All	0.888	116.361	0.000	[0.872 – 0.902]
	SB6	3 m.	0.940	134.891	0.000	[0.926 – 0.953]
		12 m.	0.940	171.336	0.000	[0.928 – 0.950]
		All	0.939	215.402	0.000	[0.930 – 0.947]