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Abstract:

Recent research has mostly examined the role of health communication technology (HCT) in patient empowerment and in producing patient-focused outcomes. This study examines HCT in a larger context where it is used as a tool to improve public health. The objective is to examine how HCT is used to monitor Covid-19's spread, and how social factors affect individual assessment of HCT and individual compliance disposition of Covid-19 guidelines. Analyzing data collected from 360 HCT users suggests that the information and system quality of HCT indeed impact users' assessment of its effectiveness and their compliance disposition. However, such effects are strongly mediated by social factors: Peer influence and government trust can sway an individual's cognitive judgments of Covid-19 regardless of HCT's impacts. The findings highlight the importance of social factors in pandemic management and the need to socialize health informatics to make them more effective.

Keywords: Health Communication Technology, Dashboard, Tracking App, Compliance, Covid-19.

1 Introduction

On December 8th, 2020, Florida armed police raided the home of Rebekah Jones, a data scientist who previously had a dispute with the state's governor over the state's Covid-19 dashboard[1]. Putting politics aside, the incident highlights the importance of a Covid-19 data dashboard in keeping citizens informed and helping policymakers manage one of the worst pandemics in recent history (Budd et al., 2020). Especially during Covid-19 lockdowns, digital technologies like data dashboards or tracking apps are critical elements in the pandemic management strategies (O'Leary, 2020; Timmers, Janssen, Stohr, Murk, & Berrevoets, 2020), being part of what researchers have called a "digital revolution" in healthcare (Keesara, Jonas, & Schulman, 2020).

These Covid-19 digital technologies are examples of health communication technology (HCT), defined as the use of the Internet and related technologies to communicate health information to the intended audiences. While prior studies have examined HCT such as telehealth (Klecun‐Dabrowska & Cornford, 2000) or patient portals (Klein, 2007), Covid-19 HCT are unique because they intend to communicate health information to the public rather than individuals (e.g., patients, physicians). During the Covid-19 pandemic, researchers have hinted at the instrumental role of HCT in public health management (Budd et al., 2020; Keesara et al., 2020; O'Leary, 2020; Timmers et al., 2020). Yet, to date, research in disaster management is still under-developed (Janssen, Lee, Bharosa, & Cresswell, 2010); and many have called for more research on the use of IS/IT in pandemic management (Ågerfalk, Conboy, & Myers, 2020; Shiau, Siau, Yu, & Guo, 2021). Furthermore, most studies in disaster management have focused on technologies that are related to planning and management (Yang, Su, & Yuan, 2012), analytics and prediction (Pietz, McCoy, & Wilck, 2020; Sheng, Amankwah-Amoah, Khan, & Wang, 2020; Tosi & Campi, 2020), or tracking and reporting (O'Leary, 2020; Rowe, Ngwenyama, & Richet, 2020; Timmers et al., 2020). There is a limited focus on HCT, and we only scratch the surface of understanding how to effectively design and use HCT to inform the public, communicate the pandemic's progress, and influence individual behaviors (e.g., compliance) (Ågerfalk et al., 2020).

Against this backdrop, the objective of this paper is to examine HCT in the Covid-19 setting, particularly when HCTs are used not only for individual benefits but also for public health management. The Covid-19 setting also provides a unique context where during long periods of lockdowns and social distance regulation, people heavily rely on public officials and social media to educate themselves about appropriate social behaviors (Ågerfalk et al., 2020; Budd et al., 2020). Thus, the influence of HCT on individual behaviors can be prominent. The paper combines studies on system quality, health beliefs, and social influence to evaluate factors that underlie Covid-19 dashboard and tracking app uses, and the extent of those technologies' effectiveness on individual compliance disposition of Covid-19 guidelines. The focal research questions are:

RQ1: what are the predictors of the effectiveness of Covid-19 HCT, and

RQ2: what are the effects of Covid-19 HCT effectiveness on compliance disposition of Covid-19 guidelines?

By answering those questions, this study contributes to the increasing but under-studied literature on IS/IT use for pandemic management (Ågerfalk et al., 2020; Shiau et al., 2021). The study focuses specifically on dashboards and tracking apps, both of which have received lesser attention compared to other technologies (Keesara et al., 2020; Shiau et al., 2021). The findings can help researchers better understand the relationship between HCT with individual compliance disposition, which has been a key element in emergency and pandemic management (Han, Ada, Sharman, & Rao, 2015). The study also aims to contribute to practice by identifying factors that contribute to the effectiveness of those technologies, which can help public managers better manage the pandemic (Budd et al., 2020).

The rest of the paper is organized as follows. First, a literature review on health technology is presented, then the research model is built. Next, our method and findings are discussed. The paper concludes with discussion of the findings and their implications for theory and practice.

[1] https://news.yahoo.com/armed-police-raid-home-florida-015603583.html

2 Literature Review

In recent years, researchers have paid more attention to health technologies and their roles in patient care and hospital services (Borrelli & Ritterband, 2015; Ricciardi, Mostashari, Murphy, Daniel, & Siminerio, 2013). Research in this stream has examined a wide range of technologies in healthcare services and how the technology can facilitate and enhance healthcare outcomes. These technologies include Internet-based patient portals to enable patients' access to their health information (Klein, 2007); electronic health record systems to digitize health records and information exchange (Abramson et al., 2012; GAO, 2014); telehealth for long distance diagnosis and advice (Cegarra-Navarro & Sánchez-Polo, 2010; Miscione, 2007); and mobile health apps for health tracking and peer support (Junglas, Abraham, & Ives, 2009; J. Zhao, Freeman, & Li, 2016).

To date, the majority of this research has focused on the impacts of health technologies on individual behaviors and hospital performance. For instance, various studies have shown that engaged patients in patient portals and/or mobile apps are likely to change their lifestyle (Leung & Chen, 2019; J. Zhao et al., 2016); or telemedicine can be associated with better service quality and patient satisfaction (Cegarra-Navarro & Sánchez-Polo, 2010). At the hospital level, ample evidence has associated health technology use with lower operational costs, lower readmission rates, and reduced delays, among other benefits (Angst, Devaraj, & D'Arcy, 2012; Bardhan & Thouin, 2013; Huerta, Thompson, Ford, & Ford, 2013; Kohli, Devaraj, & Ow, 2012; Weiner, Yeh, & Blumenthal, 2013; Wu, Kao, & Sambamurthy, 2016).

Extending these studies, this study examines the impacts of health technologies not only on individual benefits but also on community-level outcomes. Specifically, the researchers investigate the impacts of health communication technology (HCT) on individual compliance disposition of Covid-19 guidelines. These guidelines were set by public health officials to curb the spread of Covid-19 within a community and reduce the infection rate in vulnerable groups. Understanding how HCT impacts individual behaviors will inform policymakers how to better intervene for better public health management outcomes.

During the Covid-19 pandemic, a wide range of health technologies have been used to assist with the pandemic management (Budd et al., 2020; Keesara et al., 2020; Timmers et al., 2020; van der Kleij et al., 2019). To date, the majority of studies have emphasized technologies related to management, analytics, tracking and reporting activities (O'Leary, 2020; Pietz et al., 2020; Rowe et al., 2020; Sheng et al., 2020; Timmers et al., 2020; Tosi & Campi, 2020). These technologies are helpful in understanding and managing the pandemic; however, communication technologies such as dashboards and tracking apps only receive modest attention (Pietz et al., 2020; Rowe et al., 2020). This is a missed opportunity as these technologies can be the first line of defense, providing the information cues that inform the public of the severity of the disease (Ranjit, Shin, First, & Houston, 2021). Prior studies have indicated the importance of keeping the public informed to mitigate the spread of Covid-19 (Budd et al., 2020). Thus, this study aims to focus on these two technologies, dashboards and tracking apps, and to examine how the technologies can be used to influence individual behaviors for better public health management outcomes.

3 Research Model and Hypotheses Development

The research model in Figure 1 is built using two relevant theories; both have been used in health-related research before: (1) Information Systems (IS) success model (DeLone & McLean, 1992) and (2) health belief model (Hochbaum, 1958; Rosenstock, 1966). The first half of the model aims to answer the first research question while the second part answers the second question.

Our reason for integrating the two models is two-fold. First, the integrated framework compensates for the limitations of each theory and allows a more insightful investigation on health behaviors. Prior studies have called for more social aspects in technology-deterministic theories (e.g., DeLone and McLean's IS success model) (Orlikowski, 1992). These studies pointed out that technology determinants fall short in accounting for actual user behaviors (e.g., diversity in use and technology appropriation), and that the social contexts (e.g., emotions, habits, environment) surrounding an individual should be part of what drives actual user behaviors (Ahuja & Thatcher, 2005; Ortiz de Guinea & Markus, 2009). On the other hand, social cognition theories like the health belief model are primarily concerned with how individuals make sense of social situations (Conner & Norman, 2005) without much attention to how people make sense of the technology or information provided by the technology. Thus, by combining the two theories, the integrated framework transcends the limitations of each theory and allows for a complementary framework that can better explain health behaviors.

Second, the integrated framework enhances the explanatory power of Covid-19 compliance behaviors. During the Covid-19 pandemic, there was high uncertainty surrounding the nature of the viruses, the social distance guidelines, or the effectiveness of preventive measures. Subsequently, people rely on multiple sources of information to educate themselves, from official governmental websites to ad-hoc social media stories (Budd et al., 2020; Farooq, Laato, & Islam, 2020). By combining technology-deterministic and social-determinant theories, the integrated framework can examine both technology and social aspects of health behaviors during the Covid-19 pandemic, providing a more insightful examination of the phenomenon (e.g., Laato, Islam, Islam, and Whelan (2020); Rokhman, Mukhibad, Bagas Hapsoro, and Nurkhin (2022)).

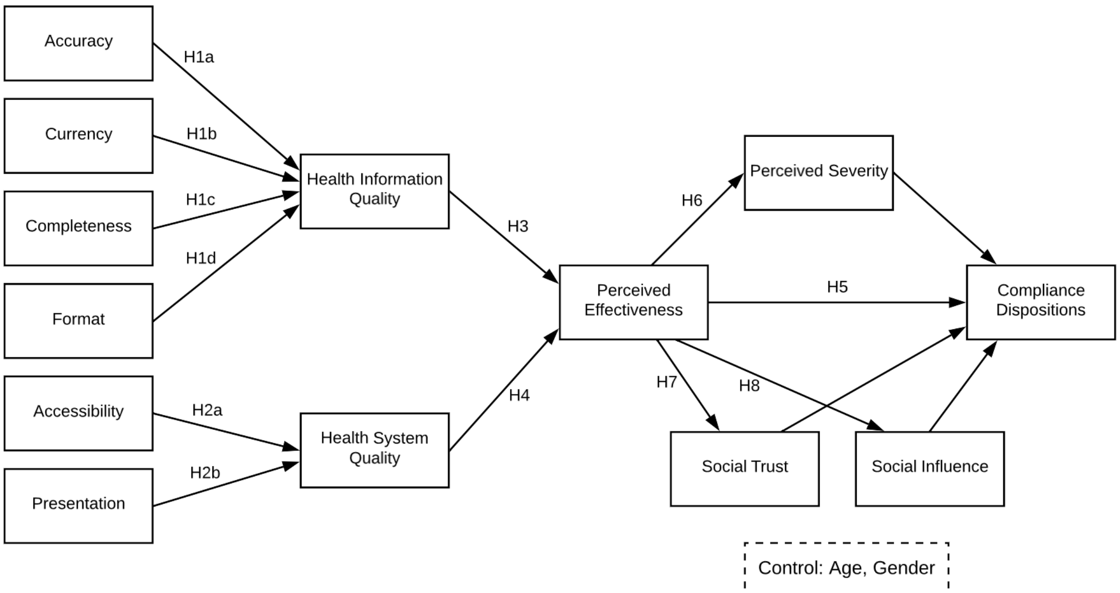

Figure 1. Research Model

3.1 Determinants of HCT Quality and Perceived Effectiveness

Understanding system quality and its impacts has long been an elusive goal within the IS discipline. Among frequently used theories, the IS success model, first proposed by DeLone and McLean (1992), is one of the most prominent. Studies have built on the model to examine determinants of system quality and how system quality influences system use and subsequent outcomes in various contexts, ranging from e-commerce (Jung-Yu, 2014; Mouakket, 2014), to e-learning portals (Ivanaj, Nganmini, & Antoine, 2019), e-service and system design (Gorla, 2012; Grange & Barki, 2020; Xu, Benbasat, & Cenfetelli, 2013), data warehouse systems (Wixom & Todd, 2005), online communities (Zheng, Zhao, & Stylianou, 2013), and health services (Liang, Xue, & Zhang, 2017).

The original IS success model posits that information quality and system quality will influence user satisfaction and user behaviors (DeLone & McLean, 1992), while subsequent studies have also added service quality as another dimension to system success (Delone & McLean, 2014). Because this study examines HCT, there is an absence of service being consumed by users. Thus, only information quality and system quality are considered. Prior research has identified a wide range of determinants for these two factors (see Table 1). In general, depending on contexts and research objectives, different determinants have been used and there is no convergence among researchers. Some researchers even go as far as proposing 12 determinants for system quality (Forsgren, Durcikova, Clay, & Wang, 2016).

Table 1. Exemplary Determinants of Information Quality and Service Quality

Construct	Determinants	Wixom and Todd (2005)	Xu et al. (2013)	Zheng et al. (2013)	Liang et al. (2017)	Grange and Barki (2020)
Information Quality	Completeness	x	x		X	
	Accuracy	x	x	x	X	
	Format	x	x	x		
	Currency	x	x	x	X	
	Transparency				X	
	Richness			x		
	Relevancy			x		
	Objectivity			x		
	Visual					x
	Navigation					x
	Page Layout					x
System Quality	Reliability	x	x		X	
	Flexibility	x	x			
	Accessibility	x	x	x	X	
	Timeliness	x	x		X	
	Navigability			x	X	x
	Presentation			x	X	x
	Integration	x				
	Security			x		
	Interactivity			x		
	Visual					x

Given the context of this study is the use of HCT for Covid-19 monitoring, it is hypothesized that the accuracy, currency, completeness, and format of the information presented in HCT will be critical for users as well as for policy makers who race against time to curb the spread of the virus. Indeed, several studies have expressed the importance of information quality to successful Covid-19 health measures (Simonov, Sacher, Dube, & Biswas, 2020; WHO, 2020). Thus, it is proposed that:

H1: Information accuracy (H1a), currency (H1b), completeness (H1c) and format (H1d) will positively influence perceived health information quality

In addition, it is hypothesized that system accessibility and presentation will be the most critical for health system quality. Because most users access a Covid-19 data dashboard or tracking app only for a short amount of time (i.e., simply retrieving the information they need), these technology interfaces are mostly simplified with a small number of pages/screens, and users can navigate through them in a few clicks. Thus, attributes such as navigability, flexibility, or interactivity are not critical. On the other hand, being able to easily access these HCTs and see a presentable interface should be critical to users' experience. Thus, it is proposed that:

H2: System accessibility (H2a) and presentation (H2b) will positively influence perceived health system quality

When a system is well built and conveys quality information, it will likely increase the user satisfaction and trust in the system (Han et al., 2015; Nicolaou, Ibrahim, & van Heck, 2013; Zheng et al., 2013); and subsequently increase the user's perceived effectiveness of the system. Perceived effectiveness refers to an individual's appraisals of whether HCT can make a difference in the overall outcome, in this case, subverting Covid-19 spread. This construct is similar to the perceived usefulness as it reflects the individual's overall appraisal of how the system can enhance task performance at hand (Ajzen & Fishbein, 1973; Ajzen, Fishbein, & Zanna, 2005). However, the perceived effectiveness also reflects an individual's belief that his/her own use of HCT can make a difference in health outcomes (e.g., flatten the curve). The concept is parallel with constructs such as perceived citizen effectiveness or perceived employee effectiveness in studies of organizational policies (Herath & Rao, 2009) or perceived effectiveness of collective action in studies of societal changes (Hornsey et al., 2006). In those studies, the perceived effectiveness reflects the individual's belief that their own actions can make a difference to a policy; thus, it is relevant to our study which focuses on Covid-19 guidelines. In this study, the perceived effectiveness can be influenced by the extent of information quality and system quality that the HCT exhibits. Thus, it is proposed that:

H3: Perceived health information quality will positively influence perceived effectiveness of the health communication technology

H4: Perceived health system quality will positively influence perceived effectiveness of the health communication technology

3.2 Relationships between Perceived Effectiveness, Social Determinants, and Compliance Disposition

As an extension of prior research, this study also examines community-level outcomes. Specifically, this study focuses on users' compliance disposition of Covid-19 guidelines. The second half of our model is built on the health beliefs model (Hochbaum, 1958; Rosenstock, 1966) to account for the relationships between perceived effectiveness, social determinants, and compliance disposition (see Figure 1).

The health beliefs model has been used in health research (Champion & Skinner, 2008; Hochbaum, 1958; Rosenstock, 1966) to explain how embedded intrinsic motivations can alter health behaviors (e.g., getting vaccinations). The original model asserts that an individual will take up action against a disease if the person holds several beliefs: 1) that she is susceptible to the disease, 2) that the disease will severely impact her life, and 3) the benefits of taking action against the disease outweigh non-action costs (e.g., inconvenience, embarrassment) (Rosenstock, 1974). Over time, the model has been extended to include various factors that can impact how people accept or reject health measures: perceived susceptibility, perceived severity, perceived benefits, perceived barriers, and self-efficacy, among others (Champion & Skinner, 2008; Strecher & Rosenstock, 1997).

The process of invoking those intrinsic motivations starts with a cue that triggers the action in focus. Such cues can be internal (e.g., perception of illness) or external (e.g., interpersonal interactions, receiving notifications from doctors) (Rosenstock, 1974). In the context of this study, it is argued that the perceived effectiveness of HCT that comes from users' experience will act as a cue that triggers the cognitive evaluation of a given scenario (e.g., Covid-19 spread) and influences the intention to exercise the expected behavior (e.g., compliance with Covid-19 guidelines). The outcome of interest is the users' compliance disposition toward Covid-19 guidelines. The users' compliance disposition refers to an individual's sense of obligation toward organizational or societal guidelines and policies (Pósch, Jackson, Bradford, & Macqueen, 2020). The construct has been widely used in criminology and cybersecurity to understand the users' willingness to obey police (Piquero & Piquero, 2006; Pósch et al., 2020) or organizational security policies (Vance, Siponen, & Pahnila, 2012). This is an important outcome given the politicized debates surrounding Covid-19 guidelines (Sherman et al., 2020; Simonov et al., 2020; WHO, 2020). Following the health belief model, this study first tests the direct effect between perceived effectiveness and compliance disposition:

H5: Perceived effectiveness of health communication technology will positively influence the user's compliance disposition

Besides the direct effect, the health belief model also includes indirect effects between the cue of action and the action of interest. The indirect effects occur through mediators such as perceived benefits, perceived susceptibility, and perceived severity, to name a few (Champion & Skinner, 2008; Strecher & Rosenstock, 1997). The relationships can be in a parallel mediation model (with no interactions between mediators), a sequential mediation model, or a moderated mediation model (Jones et al., 2015). Prior study has shown that no model empirically outperforms the others (Jones et al., 2015); and given the parallel mediation model is the original model with the most popular applications, this study opts to use it (Figure 1).

Etzioni's compliance theory suggests that compliance with organizational policies happens through three possible means: coercive compliance which relies on threats, sanctions, and penalties; normative compliance which relies on symbols, rituals, and moral gestures; and remunerative compliance which relies on salaries, benefits, and commodities (Etzioni, 1975). This study maps the coercive compliance means with perceived severity, and normative compliance means with social trust and social influence. The remunerative compliance means for Covid-19 guidelines were largely not available at the time of the study.

Perceived severity is defined as an individual's appraisal of the seriousness of a situation with regards to health consequences (Laato et al., 2020). It is the result of a cognitive process in which the individual appraises positive and negative consequences of an event before committing to a response. Studies have found perceived severity as an important predictor for compliance behaviors during the Covid-19 pandemic (Farooq et al., 2020; Laato et al., 2020). In this study's context, highly effective HCT will convey the seriousness of the situation and increase an individual's perceived severity of Covid-19. Subsequently, the perceived severity of the situation will increase an individual's compliance disposition toward Covid-19 policies. Thus, it is proposed that:

> **H6: Perceived severity of Covid-19 will fully mediate the relationship between perceived effectiveness and compliance willingness**

Given the politicized debates surrounding Covid-19 guidelines (Sherman et al., 2020; Simonov et al., 2020; WHO, 2020), this study also incorporates several social determinants to unpack the social influence related to compliance with Covid-19 guidelines. Constructs of social influence such as subjective norms (Venkatesh, Morris, Davis, & Davis, 2003) or normative pressures (DiMaggio & Powell, 1983) are commonly used in the IS literature to understand the extent to which friends and families or even institutional norms can drive one to use a technology. In a health context, social influence plays a critical role in an individual's health behaviors and well-being. For instance, social support, the care and love from members of a group, can strengthen one's mental health and resolution during difficult times (Cobb, 1976). Similarly, information gathered from our connections or government authorities can significantly sway one's opinions toward health measures (e.g., social distancing, wearing a mask). For instance, the widespread misinformation about Covid-19 has led the World Health Organization to warn of an "infodemic"—an overwhelming wave of accurate and inaccurate information—that can significantly hinder the mitigation efforts (WHO, 2020). Researchers have associated the consumption of cable news with the increase in non-compliance behaviors (Simonov et al., 2020).

This study examines two social determinants: social trust in government and social influence from peers. Social trust in government refers to the extent an individual trusts government agencies' management of health crises (Blair, Morse, & Tsai, 2017). Prior studies have shown that distrust in government hindered vaccine distribution in the measles-mumps-rubella (MMR) outbreak in the United Kingdom in the late 1990s (Larson & Heymann, 2010) and worsened the measles outbreak in Orange County, California in 2015 (Whetten et al., 2006). It is clear that in the Covid-19 pandemic, trust and distrust in government can play a crucial role in persuading individuals to comply with health measures. Because many HCTs are used by governmental agencies for public health management (e.g., Covid-19 dashboard) or use data from the government to inform users of appropriate actions (e.g., Covid-19 tracking app that tracks infection rates), the higher the quality of these technologies, the more confidence and trust the user will feel toward government's handling of the pandemic. Subsequently, higher trust and confidence will lead to higher individual compliance disposition toward Covid-19 guidelines. Thus, it is proposed that:

> **H7: Social trust in government will fully mediate the relationship between perceived effectiveness and compliance willingness**

In addition, it is hypothesized that social influence from peers can also impact an individual's compliance with health measures. Social influence from peers refers to the extent of pressure from families and friends that can sway an individual to engage or not engage in certain behaviors (e.g., complying with health measures) (Ajzen & Fishbein, 1973; Ajzen et al., 2005). When HCT effectively conveys the information related to Covid-19 (e.g., infection rates, death rates, vaccination progress), users will become more informed. When this happens, peer pressure builds up as people urge friends "to do the right things," or neighbors encourage compliance for "the sake of the community." Subsequently, this creates a network effect and changes an individual's compliance disposition. Researchers have found social influence from peers is among predictors of whether one would take a Covid-19 vaccine when it is available (Sherman et al., 2020). Thus, it is proposed that:

> **H8: Social influence from peers will fully mediate the relationship between perceived effectiveness and compliance willingness**

4 Method

4.1 Sample and Procedure

This study examines factors that influence users' perception of the effectiveness of HCTs and how that impacts their compliance disposition toward public health measures (see Figure 1). Particularly, the study focuses on HCT that are instrumental to the monitoring of Covid-19 spread: the Covid-19 data dashboard and the tracking app (Budd et al., 2020).

Prior to the distribution of the main study survey, we conducted a pre-test which pre-screens the respondents who either 1) use a tracking app and 2) who use a dashboard. We gathered the IDs of respondents who qualify for the main survey based on their pre-test responses and only distributed the main study survey to them. Those who responded as individuals who only used tracking apps will be given the survey that pertains to the tracking app and vice versa.

The main study survey data were gathered between October and November 2020. During these months, there was a spike of COVID-19 cases around the US (Adeline et al., 2020). Survey items were developed based on measurement scales from prior studies (see Appendix 1). All measurements were based on a 7-point Likert scale (1=Strongly disagree; 7= Strongly agree). Three hundred and sixty questionnaires were gathered through an online crowdsourcing platform, Prolific.ac ($n_{dashboard}$=178; n_{app}=182). This crowdsourcing platform is widely used among the scientific community and claims to have high reliability (Palan & Schitter, 2018). All respondents surveyed were individuals who have had experience using HCTs (dashboard or tracking app) at least once. Examples of the tracking app or the dashboard were provided (e.g., CDC mobile app, WHO dashboard, and other regional apps). Respondents were screened based on two questions: Do you live in the United States? Have you had experience using health dashboards/applications? Appendix 2 shows the demographics of respondents.

4.2 Data Analysis

The predicted hypotheses were tested using partial least squares structural equation modelling (PLS-SEM). PLS-SEM is appropriate for this study as it allows the simultaneous estimation of multiple causal relationships between one of more independent variables and one dependent variable (Joe F. Hair, Ringle, & Sarstedt, 2011). In addition, PLS-SEM is used due to its ability to estimate complex models with many constructs, including indicator variables and structural equation paths without imposing distributional assumptions on the data (Joseph F. Hair, Risher, Sarstedt, & Ringle, 2019).

The total sample size was 360 which is sufficient for our model (Joe F. Hair et al., 2011). Two control variables were tested: age and gender. Results showed that gender has no significant impact on the model $F(1, 359)=.42$, p=n.s. However, age has a significant impact on perceived effectiveness and compliance disposition $F(4, 359)=5.84$, $p<.001$. A post-hoc analysis was conducted to investigate the impact of age on the overall model.

Reliability, convergent validity and discriminant validity tests were conducted (see Table 2). Composite reliability (CR) and Cronbach Alpha (α) were above the threshold of .70, which suggests that the constructs are reliable (Bagozzi & Yi, 1988). Convergent validity was confirmed as all AVE value was above the threshold of .05 (Fornell & Larcker, 1981). Discriminant validity was established through two methods. The first method is to examine whether each construct's AVE square root was greater than its highest correlation with other constructs (known as Fornell-Larcker criterion). The second is to check whether each indicator outer loadings on its assigned construct were greater than its cross-loadings with other constructs. Multi-collinearity was also examined through the variance inflation factor (VIF) and all were below the threshold of 5 (Joe F. Hair et al., 2011), and the tolerance level was above 0.2. These results show strong evidence for the reliability and validity of construct measures.

Table 2. Discriminant validity (Fornell-Larcker Criterion)

	ACCU	ACCES	CURR	EFFEC	INFO	PRES	QUAL	CODI	COMPL	FORM	SEVERE	SOCAL	STRUST
ACCU	0.75												
ACCES	0.71	0.84											
CURR	0.80	0.78	0.83										
EFFEC	0.69	0.60	0.67	0.84									
INFO	0.76	0.63	0.70	0.80	0.93								
PRES	0.69	0.75	0.67	0.60	0.60	0.84							
QUAL	0.74	0.75	0.77	0.72	0.76	0.70	0.94						
CODI	0.24	0.18	0.24	0.26	0.26	0.21	0.27	0.70					
COMPL	0.70	0.56	0.65	0.64	0.71	0.59	0.7	0.36	0.92				
FORM	0.72	0.82	0.74	0.59	0.62	0.71	0.73	0.19	0.58	0.89			
SEVERE	0.23	0.14	0.19	0.30	0.29	0.14	0.26	0.21	0.25	0.14	0.91		
SOCIAL	0.39	0.35	0.37	0.40	0.38	0.45	0.36	0.52	0.40	0.29	0.18	0.84	
STRUST	0.37	0.28	0.35	0.33	0.42	0.29	0.41	0.49	0.45	0.33	0.11	0.39	0.91
Cronbach α	*.79*	*.92*	*.86*	*.90*	*.93*	*.80*	*.94*	*.72*	*.91*	*.88*	*.90*	*.90*	*.91*
CR	*.83*	*.96*	*.90*	*.93*	*.95*	*.88*	*.96*	*.80*	*.94*	*.93*	*.94*	*.92*	*.94*
AVE	*.71*	*.72*	*.70*	*.72*	*.87*	*.72*	*.89*	*.52*	*.85*	*.81*	*.83*	*.71*	*.84*

Notes:
CR: Composite Reliability; AVE: Average Variance Extracted
ACCU: Accuracy; ACCES: Access; CURR: Currency; EFFEC: Perceived Effectiveness; INFO: Information Quality; PRES: Presentation; QUAL: System Quality; CODI: Compliance Disposition; COMPL: Completeness; FORM: Format; SEVERE: Perceived Severity; SOCAL: Social influence; STRUST: Social trust

The questionnaire gathered via the crowdsourcing platform is designed with pre-screening questions as well as with forced responses. Thus, non-response bias is not available. To further determine the possibility of non-response bias, a procedure known as wave analysis (comparing late and early responders) was conducted. The findings indicate that there was no significant difference ($p<.05$) between the late and early responders on all the constructs. In addition, a Mann-Whitney U test was used to compare early and late respondents on the entire sample. The findings indicated no significant difference between the two groups on the dependent variables.

Two approaches were used to examine common method bias. First, the CFA marker technique (Williams, Hartman, & Cavazotte, 2010) was used. This method introduces a marker latent variable with scale items that share identical characteristics with those that measure relevant constructs. Two models are then compared: one with common method factor and the other one with marker variable. Comparison of each item's path coefficient from its latent to its path coefficient from the former model indicated a lower path coefficient from the latter model ($\beta_{\text{without marker}}$=.64; $\beta_{\text{with marker}}$=.55). The variance explained by the substantive factors (that is, not on the common method factor) was much larger than the variance explained by the common method factor which is an indication that common method bias was unlikely presented. The second approach used the VIF approach in PLS-SEM (Kock, 2015). Based on a full collinearity test, the VIFs obtained for all the latent variables in the model are all smaller than the threshold of 3.3, indicating no issue from common method bias.

5 Findings

5.1 Evaluation of the Structural Model

The structural model from the PLS analysis shows the percentages of the explained variance (R^2) for effectiveness of HCT, information quality, system quality, compliance, perceived severity, social influence and social trust are .67, .66, .61, .39, .01, .16, and .11, respectively. In addition to the R^2, the model looks at the Q^2 predictive relevance of the exogeneous constructs (Woodside, 2013). Q^2 values that are greater than zero indicate that the model has predictive relevance. The blindfolding technique is used to perform this test: perceived effectiveness (Q^2 =0.48), information quality (Q^2 =.56), system quality (Q^2 =.54), compliance disposition (Q^2 = .18), perceived severity (Q^2 =.01), social influence (Q^2 =.11), and social trust (Q^2 =.01). To confirm the overall fit of the PLS path model, the composite-based standardized root mean square residual (SRMR) was examined. The model produces a value of 0.07, which is below the threshold of 0.10 (Joe F. Hair, Sarstedt, Ringle, & Mena, 2012; Henseler, Ringle, & Sarstedt, 2015).

A nonparametric bootstrap analysis of 5,000 subsamples and 360 cases revealed the proposed relationships (Table 3). Hypothesis 1abc, which predicted that there is a positive relationship between information accuracy, currency, completeness and heath information quality were supported (β=.39, p<.01; β=.15, p<.01; β=.31, p<.01, respectively). The information format did not have a significant impact on health information quality (H1d). H2ab, which predicted that system accessibility and presentation have a positive impact on health system quality, were supported (β=.52, p<.01; β=.31, p<.01, respectively). Hypothesis 3 and 4 predicted a positive impact of health information quality (H3) and health system quality (H4) on perceived effectiveness. Both were supported (β=.61, p<.01; β=.25, p<.01, respectively). H5 which predicted that perceived effectiveness has a positive impact on compliance disposition was not supported.

Next, since there are two groups that are being measured in the model, the data groups were defined: dashboard versus tracking app. When running the bootstrap analysis, the data groups were selected to be included in the analysis. Bias-corrected and Accelerated (BCa) bootstrap was selected for the calculation.

Table 3. Two-groups Path Analysis

Hypothesis	Path	Overall Model	Dashboard	Tracing App
H1a	Accuracy→ Information Quality	.39***	.43***	.40***
H1b	Currency→ Information Quality	.15***	.00 n.s.	.27***
H1c	Completeness→ Information Quality	.31***	.31***	.29***
H1d	Format→ Information Quality	.05 n.s.	.12 n.s.	.08 n.s.
H2a	Accessibility→ System quality	.52***	.54***	.51***
H2b	Presentation→ System quality	.31***	.30***	.32***
H3	Information Quality → Perceived Effectiveness	.61***	.51***	.67***
H4	System Quality→ Perceived Effectiveness	.25***	.30***	.21**
H5	Perceived Effectiveness→ Compliance Disposition	.04 n.s.	.20 n.s.	.29***
Note: <.10*, <.05**, <.01***				

Table 3 also presents the result of hypotheses testing for each type of technology. For the health data dashboard, H1ac which predicted a positive impact between information accuracy (H1a) (β= .43 , p<.01), information completeness (H1c) (β=.31, p<.01), and health information quality were supported. Information currency (H1c) and format (H1d) did not have a positive effect on health information quality. H2ab which predicted accessibility and presentation have a positive impact on health system quality were supported (β=.54, p<.01; β=.30, p<.01, respectively). Hypothesis 3 and 4 which predicted a positive impact of health information quality (H3) and health system quality (H4) on perceived effectiveness were also supported (β=.51, p<.01; β=.30, p<.01, respectively). H5 which predicted that perceived effectiveness has a positive impact on compliance disposition was not supported.

Regarding the use of a health tracking app, Table 3 shows that hypothesis 1abc, which predicted a positive impact between information accuracy (H1a) (β= .38 , p<.01), currency (H1b) (β=.30 , p.<.01), completeness (H1c) (β=.30, p<.01) and health information quality, were supported. Just like the dashboard, information format (H1d) also did not have a positive effect on information quality. H2ab, which predicted that system accessibility (H2a) and presentation (H2b) have a positive impact on health system quality, were supported (β=.51, p<.01; β=.32, p<.01). Hypothesis 3 and 4 which predicted a positive impact of health information quality (H3) and health system quality (H4) on perceived effectiveness were both supported (β=.67, p<.01; β=.21, p<.01, respectively). Similar to the dashboard results, H5 was not supported.

5.2 Mediation Effects

The overall mediation effect was investigated by measuring the total effect, direct effect and indirect effect of the mediators when included in the model (see Table 4). The results show that including the mediators in the model makes it a better fit than not including the mediators in the model. More specifically, the mediators, such as social trust and social influence, boost the overall fit of the model.

A second method of mediation analysis was also conducted. A bootstrap mediation analysis was performed using the approach and syntax provided by Preacher and Hayes (2008), which has been argued to be a superior approach for mediation analysis (X. Zhao, Lynch, & Chen, 2010). Social trust (H7) and social influence (H8), and perceived severity (H6) were included in the model as mediators. The mediation effect of the overall model is shown in table 4. As can be seen, perceived effectiveness has a significant total effect on compliance disposition (c=.27, t=4.61, p<.001). When including the mediators, perceived effectiveness has a decreased effect and has become insignificant on compliance. In other words, while the individuals find the HCTs to be effective, they need to be convinced by their social surroundings (i.e. social influence) and governmental trust (i.e. social trust) in order for them to comply with any public health measures (e.g. wearing of masks).

Table 4. Mediation Results of Overall Model

Model A Total Effect (c)			**Model B Direct effect (c')**			**Model B Indirect effects**			
Path	Coefficient	t-value	Path	Coefficient	t-value	Path	Coefficient	Bias corrected bootstrap 95% confidence interval	
								Lower	Upper
EFF→ CODI	.27***	4.61		.04 n.s.	.58	Total	.30***		
						via SEV	.03 n.s.	.06	.09
						via SOCIAL	.17***	.13	.27
						via STRUST	.15***	.09	.21

Note: EFF: Effectiveness, CODI: Compliance Disposition, SEV: Perceived Severity, STRUST: Social Trust; SOCIAL: Social Influence. Bootstrapping 15% confidence interval based on 5000 samples.

5.2.1 Health Dashboard

In addition, further analysis using the Preacher, Rucker, and Hayes (2007) method was conducted to determine the mediation effect between the two types of modalities (see Table 5). A 5,000 bias-corrected (BC) bootstrapping sample at the 95 BC confidence level was used to determine the mediation effects (Shrout & Bolger, 2002).

Social Influence: the results show that perceived effectiveness has a positive impact on social influence (β=.54, t(5.57), p<.01); and social influence has a positive impact on compliance disposition (β=.39, t(8.35), p<.01). Next, with the presence of social influence as a mediator, perceived effectiveness does not have a positive impact on compliance disposition. This suggests that social influence serves as a full mediator.

Social Trust: perceived effectiveness has a positive impact on social trust (β=.39, t(5.59), p<.01) and social trust has a positive impact on compliance disposition (β=.47, t(6.96), p<.01). The significance of perceived effectiveness on compliance remains positively significant while social trust as a mediator is present in the model (β=.15, t(2.07), p<.05). This suggests that social trust is a partial mediator in the relationship. The indirect effect of social trust on an individual's compliance disposition of public health measures was stronger (β=.18, SE=.05, 95% CI [.10, .29]) than the direct effect (β=.14, SE=.07, 95% CI [.01, .28]).

Perceived Severity: perceived effectiveness has a positive impact on perceived severity (β=.29, t(3.93), p<.01); but perceived severity does not have a positive impact on compliance disposition (β=.14, t(1.92), p=n.s.). There is a direct effect of perceived effectiveness on compliance disposition (β=.32 , t(4.59), p<.01). This suggests that perceived severity does not serve as a mediator for the hypothesized relationship for the dashboard.

5.2.2 Health Tracking App

Social Influence: perceived effectiveness has a positive impact on social influence (β=.43, t(5.75), p<.01); and social influence has a positive impact on compliance disposition (β=.34, t(6.35), p<.01). When social influence as a mediator is introduced, perceived effectiveness loses its significant impact on compliance disposition. This suggests that social influence serves as a full mediator.

Social Trust: perceived effectiveness has a positive impact on social trust (β=.19, t(3.16), p<.01); and social trust has a positive impact on compliance disposition (β=.39, t(5.95), p<.01). The significance of effectiveness on compliance loses its significance when social trust as a mediator is present in the model. This suggests that social trust is a full mediator in the relationship.

Perceived Severity: perceived effectiveness has a positive impact on perceived severity (β=.26, t(4.29), p<.01); but perceived severity does not have a positive impact on compliance disposition (β=.14, t(1.92), p=n.s.). There is a direct effect of perceived effectiveness on compliance disposition (β=.14, p<.05). This suggests that perceived severity does not serve as a mediator for the hypothesized relationship.

Although perceived severity did not have a mediating effect when tested based on the individual modality, perceived severity serves as a partial mediator when measured in the general model. The results show that, not dependent on the technology modality, there is a positive significant impact of perceived effectiveness on perceived severity (β=.27, t(6.01), p<.01); perceived severity has a significant positive impact on compliance disposition (β= .14, t(2.70), p<.01); and there is a direct impact of perceived effectiveness on compliance disposition (β=.19, t(4.19), p<.01). This result suggests that perceived severity is a partial mediator between perceived effectiveness and compliance disposition. Between the direct and indirect effects, the mediator seems to weaken the relationship when it is introduced in the indirect relationship (β=.04, SE=.02, 95% CI [.01, .07]) compared to the direct relationship (β=.19, SE=.05, 95% CI [.10, .28]).

Table 5. Two-group Mediation Results

Hypothesis	Path	Dashboard	Tracking App	Supported?
H6	EFF (X)→ PSERV (M)→CODI (Y)			
	X → M	.28***	.26***	No
	M→ Y	.14 n.s.	.14 n.s.	
	Indirect: X→Y	.29***	.10 n.s.	
	Direct: X→ Y	.32***	.14**	
H7	EFF (X)→ Social Trust (M)→CODI (Y)			Yes
	X → M	.39***	.19***	
	M→ Y	.46***	.39***	
	Indirect: X→Y	.14**	.06 n.s.	
	Direct: X→Y	.32***	.14**	
H8	EFF (X)→ Social Influence (M)→CODI (Y)			Yes
	X → M	.54***	.39***	
	M→ Y	.39***	.34***	
	Indirect: X→Y	.11 n.s.	.01 n.s.	
	Direct: X→Y	.32***	.14**	

Note: EFF: Perceived Effectiveness, CODI: Compliance Disposition; PSERV: Perceived Severity
X= Independent variable, M= Mediator; Y= Dependent variable

5.3 Post Hoc Analysis

The mediation results show that both social trust and social influence had an indirect effect on perceived effectiveness and an individual's compliance disposition. Since perceived severity did not have an indirect effect on the predicted relationship (effectiveness→compliance disposition), further analysis was conducted to determine if there is a relationship among the mediators. A correlation analysis was conducted. The results show that there is a weak relationship between perceived severity and social trust of the government (r=.12, p<.05) and social influence (r=.19, p<.01). This suggests that the more Americans perceive the pandemic as severe, the more they will trust the government and their social circle. Between the government and their social circle, Americans trust their social circle (e.g., friends and families) more than themselves or the government.

According to the Centers for Disease Control and Prevention (CDC, 2020), Covid-19 risk is related to age. The results indicate that age has an impact on the overall model. Thus, a post-analysis was conducted in which data were split into two main age groups, (1) 18-34 and (2) 35-65, according to the risk level as indicated by CDC. Based on the path analysis, the main differences between the two age groups are the perceived effectiveness and their compliance disposition ($\beta_{18\text{-}34}$ =.48, p<.01; $\beta_{35\text{-}65}$ =.02, p=n.s.). This result is rather interesting as it poses a different image of how media portray the younger age group and their attitude towards Covid-19 and its impact on their health. However, it is important to note that individuals in the younger age group may be more tech savvy when compared to the older group. Thus, it is inevitable that older group individuals may be reliant on other sources such as their social community.

6 Discussion

Globally, governments as well as organizations are increasingly relying on HCTs to improve their pandemic management strategies (Budd et al., 2020; Keesara et al., 2020; Timmers et al., 2020). The purpose of this study was to understand the factors that affect individuals' perception of the effectiveness of HCT and how that perception will impact their compliance disposition toward public health guidance (e.g., wearing masks). Using data collected from 360 users of a Covid-19 data dashboard and tracking app, our findings show a significant relationship between perceived effectiveness and compliance disposition for tracking app users but not dashboard users (H5). More interestingly, social factors have an even stronger effect on individuals' tendency to comply regardless of how information is delivered through HCT. Specifically, social factors such as social trust of government (H7) and social influence from peers (H8) can act as mediation between perceived effectiveness and compliance disposition. Among determinants of information quality and system quality, information accuracy, completeness, system accessibility, and system presentation emerge as significant predictors across both technologies. Table 6 provides a summary of our findings.

Our study contributes toward existing literature on HCT by highlighting the transformation of the traditional patient-doctor relationship to user-doctor-government relationship in regards to the use of HCT. The promise of HCT in a disaster setting is to empower users through accessible information, and in so doing, improving the communication of public health information. Additionally, our study highlights the features that users deemed important, which could serve as a guide for the development of other HCT in disaster management.

Table 6. Summary of Results

Hypothesis	Path	Supported?	Implications
H1a	Accuracy→ Information Quality	Yes	▪ In health emergency situations, users are more concerned with the substance rather than the format of the information ▪ Call for more studies of how users perceive and handle information differently in health-related emergencies
H1b	Currency→ Information Quality	Only for tracking app	
H1c	Completeness→ Information Quality	Yes	
H1d	Format→ Information Quality	No	
H2a	Accessibility→ System quality	Yes	▪ In health emergency situations, users highly value the accessibility and presentation of information in HCT
H2b	Presentation→ System quality	Yes	
H3	Information Quality → Perceived Effectiveness	Yes	▪ HCT is an important element of public health management, particularly in informing the public and helping to change compliance disposition
H4	System Quality→ Perceived Effectiveness	Yes	
H5	Perceived Effectiveness→ Compliance Disposition	Only for tracking app	
H6	Mediator: Perceived Severity	No	▪ Social factors play important roles in health-related emergencies. They mediate the influence of perceived effectiveness of HCT on an individual's compliance disposition ▪ To get more compliance from individuals, health officials can reach out to community leaders (e.g., church pastors, celebrities) to exert influence through prominent figures in the community
H7	Mediator: Social Trust	Yes	
H8	Mediator: Social Influence	Yes	

6.1 Implications to Theory

The paper makes several contributions to theory. First, we contribute to the under-developed research on IS/IT uses in emergency situations (Ågerfalk et al., 2020; Shiau et al., 2021), and in particular, to the research on dashboards and tracking apps which is under-studied compared to other HCT (Keesara et al., 2020). The findings respond directly to calls for more research on behavior aspects of pandemic management (Ågerfalk et al., 2020) by identifying several social determinants that can impact the effectiveness of HCT on compliance behaviors. In addition, the findings show that information accuracy and completeness but not information format are critical for the perceived quality of HCT, indicating that in health emergency situations users are more concerned with the substance rather than the format of the information. This is in contrast with situations in which users handle non-urgent information (e.g., data warehouse processing (Wixom & Todd, 2005), e-service (Xu et al., 2013), virtual community (Zheng et al., 2013)); thus, it suggests that users are likely to perceive and handle information differently for health-related emergencies (c.f., Liang et al. (2017)).

Second, the study extends prior research on health technologies and IS success model research by examining both individual outcomes and community-level outcomes. To date, most studies have only focused on individual and hospital-level outcomes (Angst et al., 2012; Huerta et al., 2013; Leung & Chen, 2019; Weiner et al., 2013; Wu et al., 2016; J. Zhao et al., 2016). Given the lack of research on disaster management (Janssen et al., 2010) and the rise of digital technologies in managing the Covid-19 pandemic (Keesara et al., 2020; Timmers et al., 2020), this study illustrates HCT can be an important element of public health management, particularly in informing the public and helping to change compliance disposition. We encourage future studies to scrutinize this important topic.

Third, the paper combines social factors and technology factors to understand compliance disposition in a pandemic situation. Prior studies built on the popular IS success model (DeLone & McLean, 1992) have indicated that an individual's appraisals of technology characteristics can predict behavioral outcomes. Yet, many have called for more social considerations in such technology-deterministic theories (Ahuja & Thatcher, 2005; Ortiz de Guinea & Markus, 2009), and in the context of the Covid-19 pandemic, it is unknown how this theory would be applicable where social dynamics can sway individual behaviors (Blair et al., 2017; Cobb, 1976; Laato et al., 2020; Larson & Heymann, 2010). This paper extended the technology-deterministic model of the IS success model by incorporating the health belief model to investigate individuals' compliance disposition toward health safety measures. While perceived severity did not have a mediating effect on the hypothesized relationship, the results did show that social trust toward the government and social influence had a mediating effect on the hypothesized relationship. These results indicate that people are still very much influenced by their social surroundings especially when the message is being amplified on social media.

Lastly, the findings illustrate the significance of social determinants in a pandemic situation. While perceived effectiveness can influence an individual's compliance disposition through the use of a tracking app, the effect is fully mediated by social determinants (i.e., social trust and social influence). This finding echoes recent studies which suggest that peer influence will play an important role in Covid-19 vaccination (Sherman et al., 2020). While recent studies have called for more attention to emerging technologies and health research (Agarwal, Dugas, Gao, & Kannan, 2020; Agarwal, Guodong, DesRoches, & Jha, 2010), this paper advocates for a scrutiny of the dynamics between technology and social factors in order to fully understand how specific outcomes come about. Doing so will potentially explain why HCT delivers expected outcomes in some contexts but not in others (Borrelli & Ritterband, 2015; Bui, Hansen, Liu, & Tu, 2018).

6.2 Implications to Practice

The findings also make several contributions to practice. First, while information quality and system quality do impact an individual's perception of HCT, such perception is fully mediated by social factors (i.e., social trust and social influence). While social trust is inherent to an individual and is difficult to change, social influence is more likely influenced by external factors and can offer policy makers a venue to change individual behaviors. In light of recent debates surrounding Covid-19 compliance and safety measures (Laato et al., 2020; Sherman et al., 2020; Simonov et al., 2020), this finding implies that to get more compliance from individuals, health officials can reach out to community leaders (e.g., church pastors, celebrities) to exert influence through prominent figures in the community. Digital ad campaigns in social media are another strategy to mobilize public support and encourage compliance.

Second, the findings are aligned with prior studies that social trust in government is a key to compliance behaviors in a pandemic (Blair et al., 2017; Larson & Heymann, 2010; Whetten et al., 2006). While it is difficult and time-consuming to alter social trust, health officials should try different initiatives to increase such trust for better community support during emergency situations. For instance, by increasing transparency and communication to foster community interaction and trust. Recently, studies have suggested that a policy dashboard in combination with a data dashboard can increase the transparency of government's handling of the pandemic, thus increasing public trust in the government (Head, 2020).

6.3 Limitations and Future Research

The results of this study are not without limitations. These limitations however suggest directions for future research. The extant literature has highlighted the impact of perceived severity (Champion & Skinner, 2008) on individuals' willingness to accept or reject health measures. The present research instead shows that there is no mediating effects between an individual's perceived effectivess and their compliance disposition toward health measures. Future research could investigate the mediating perceived benefit of HCT to assess its impact on individuals' compliance disposition toward public health measures. Other personal traits such as personal risk tolerance or political leaning can also be added to provide a better understanding of the model.

Another limitation is the age of the respondents. The respondents gathered were between 18-65 years of age. Individuals who are above 65 years of age may have a different compliance behavior due to their life experience (e.g. influenza) and their level of technology literacy. Future research could address the older age group in regards to their attitude and behavior toward complying with public health safety measures. Another limitation to consider is the homegenity of the sample. This current study is fairly homegenous based on the ethnicity. It would be beneficial to replicate the model on a hetergenous sample to detemine if there is a difference in result. For a hetergenous sample, a larger sample is necessary. While the education level and age varies in this study, a contribution toward future research could be to recruit respondents with different medical histories.

Based on the number of cases reported around the world, countries that are flattening the curve indicate a different behavior protrayed by their residents. Thus, an area of exploration for this study is to replicate this study in a different country that has a different culture (e.g. collectivitic versus individualistic). In addition, duplication of our study in contexts that are similar to the Covid-19 pandemic (e.g., high uncertainty situations like war or natural disasters) will be usful to confirm/disconfirm our findings here.

Another limitation is the excluding from the sample those who did not have the tracking app downloaded or have not used the dashboard for tracking purposes. The reason for these individuals not engaging with these technologies may have an implication on their compliance disposition. Future research could include these group of individuals' perceptions of these technologies (e.g., information and system quality), as well as inquiring about their compliance disposition.

Lastly, the study only examined compliance disposition instead of actual compliance behaviors. Due to the highly politicized debates surrounding compliance at the time of the study, measuring and mapping compliance behaviors to the model became difficult. Future research can look into whether HCT uses and social determinants can change actual compliance behaviors for a less politicized disease.

7 Conclusion

As a consequence of the increasing number of COVID-19 cases around the world, the attention of researchers and practitioners is moving toward the development of HCT to monitor and track active cases in the community. Accordingly, this study investigates two types of HCT: dashboards and tracking apps among active users. The results of our study respond to the need for further evidence on how HCT affect different groups of people (e.g., occupation, culture). Overall, the evidence from the present research contributes to previous IS literature and to the public health debate by relating to individuals' compliance disposition based on both social and technology factors, rather than just focusing on the mere technology acceptance. Furthermore, the present research includes considerations from psychology in addressing how individuals might behave in the interaction with their social surroundings by specifically accounting for psychological reactance and self-evaluation of the effectiveness of HCT..

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Appendix A: Survey Instrument

Construct	Loading
Access (Wixom & Todd, 2005)	
ACCES1: The technology allows information to be readily accessible to me	.85
ACCES2: The technology makes information very accessible	.87
ACCES3: The technology makes information easy to access	.86
ACCES4: It is easy to navigate through the technology	.81
ACCES5: The overall layout of the technology is clear	.85
Currency (Wixom & Todd, 2005)	
CURR1: The technology provides me with the most recent information	.84
CURR2: Health information from the technology is mostly up to date	.84
CURR3: The technology acknowledges my actions quickly (e.g., confirmation message) (reverse coded)	.81
CURR4: The speed by which information is displayed by the technology is fast enough (reverse coded)	.79
Accuracy (Wixom & Todd, 2005)	
ACCU1: The technology provides correct health information	.91
ACCU2: Online health information from the technology is accurate	.87
ACCU3: It is easy to read the information from the technology	.75
Completeness (Wixom & Todd, 2005)	
COMPL1: The technology provides me with a complete set of health information	.93
COMPL2: The technology produces comprehensive health information	.92
COMPL3: The technology provides me with all the health information I need	.90
Format (Wixom & Todd, 2005)	
FORM1: The information provided by the health technology is well formatted	.91
FORM2: The information provided by the health technology is well laid out	.99
FORM3: The information provided by the health technology is clearly presented on the screen	.91
Presentation (van den Hooff, 2005)	
PRES1: Pictures and colors used in the technology are attractive	.81
PRES2: The information on the technology is presented appropriately	.90
PRES3: The technology is presented with appropriately sized fonts	.83
Information Quality (Wixom & Todd, 2005)	
INFO1: Overall, I would give information from the technology high marks	.94
INFO2: Overall, I would give information from the technology a high rating in terms of quality	.93
INFO3: In general, the technology provides me with high-quality health information	.93
System Quality (Wixom & Todd, 2005)	
QUAL1: In terms of system quality, I would rate the technology highly	.94
QUAL2: Overall, the technology is of high quality	.94
QUAL3: Overall, I would give the quality of the technology a high rating	.95
Perceived Effectiveness (Herath & Rao, 2009; Moriuchi, 2021)	
EFFEC1: This technology was effective in informing me the current situation of the pandemic	.88
EFFEC2: This technology was effective in delivering accurate information	.88
EFFEC3: This technology was effective in providing clear information to the community to help flatten the curve of the pandemic	.86
EFFEC4: This technology can make a difference in helping to flatten the curve of the pandemic.	.81
EFFEC5: If I follow the instructions in the technology, I can make a difference in helping to reduce the number of Covid-19 cases in my organization.	.81
Social Trust (Blair et al., 2017)	
STRUST1: I believe that our government is willing to provide adequate health care treatment for Covid-19 patients	.93
STRUST2: I believe that our government is able to provide adequate health care treatment for Covid-19 patients	.89
STRUST3: I trust our government in providing adequate health care treatment for Covid-19 patients	.94
Perceived Severity (Farooq et al., 2020)	
SEVERE1: The negative impact of Coronavirus (COVID-19) on my health is very high	.88
SEVERE2: Coronavirus (COVID-19) can be life-threatening on my health	.92
SEVERE3: The Coronavirus (COVID-19) is a serious health threat for someone like me	.93
Social influence (Ajzen et al., 2005)	
In regards to the tracking app/dashboard…	
SOCAL1: My peers expect me to use the health assessment technology	.82
SOCAL2: My peers want me to use frequently	.86
SOCAL3: Generally speaking, I try to do what my peers think I should do	.82
SOCAL4: My family want me to use frequently	.87

SOCAL5: Generally speaking I try to do what my family think I should do	.94
Compliance Disposition (Pósch et al., 2020)	
WILL1: I only obey the authorities handling the Coronavirus because I am afraid of them.	.89
WILL2: People like me have no choice but to obey the law enforcers/health enforcers.	.76
WILL3: I feel a moral duty to support the decisions of law enforcers/health enforcers, even if I disagree with them.	.65
WILL4: I feel a moral duty to obey the instructions of law enforcers/health enforcers, even when I don't understand the reasons behind them.	.68

Appendix B: Respondent Demographics

Demographics	**Dashboard**	**App**
Gender		
Male	52.8	63.2
Female	47.2	36.5
Prefer not to say	-	.5
Employment		
Employed full time	77.0	92.3
Employed part time	11.2	4.4
Unemployed looking for work	3.9	-
Unemployed not looking for work	2.2	-
Retired	.6	-
Student	4.5	2.7
Disabled	.6	.5
Age		
18 – 24	8.4	10.4
25 – 34	41.0	52.7
35 – 44	25.8	25.3
45 – 54	22.5	11.0
55 – 64	2.2	.5
Educational Level		
Less than high school	.6	-
High school graduate	4.5	3.3
Some college	11.8	6.6
2-year degree	3.9	7.1
4-year degree	33.1	43.4
Professional degree	42.7	33.5
Doctorate	3.4	6
Experience using e-health technology		
Last week	38.8	31.3
Last month	18	36.8
Last 3 months	43.3	28.6
Last 6 months	-	3.3

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