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Fostering participation in digital public health interventions: The case of digital contact tracing

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DISCUSSION PAPER

// DOMINIK REHSE AND FELIX TREMÖHLEN

Fostering Participation in Digital Public Health Interventions: The Case of Digital Contact Tracing

Fostering participation in digital public health interventions: The case of digital contact tracing

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Abstract

The SARS-CoV-2 pandemic has made all the more clear that public health is a public good. Public health interventions try to encourage contributions to this public good. Digital public health interventions are increasingly being used to complement traditional public health interventions. The rollout of digital contact tracing apps during the SARS-CoV-2 pandemic is a prominent example. We review the literature on how participation in such digital public health interventions could be fostered, provide an overview of digital contact tracing as one such intervention, provide policy recommendations on how to increase its adoption and usage as well as recommendations for further research.

Keywords: Public health, Public good, Public health intervention, Digital contact tracing

JEL classification: H41, I12, I18

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1. Introduction

The beginning of the 2020s has been shaped by a major worldwide health crisis: the SARS-CoV-2 pandemic. As of end of October, 2020, about 45.67 million infections with the new coronavirus and about 1.19 million deaths of people tested positive for the virus have been reported worldwide (Johns Hopkins University, 2020), by far exceeding 8,096 reported infections and 774 deaths attributed to the SARS-CoV-1 pandemic of 2002 and 2003 (WHO, 2003). In the absence of effective pharmaceutical interventions and of sufficient testing and tracing capacities, many governments repeatedly turned to limiting freedom of movement in order to contain the spread of the virus. However, school and business closures, social distancing, travel restrictions, mandatory quarantine and other drastic measures triggered significant adverse social and economic effects (Deb et al., 2020; Mulligan, 2020). As a consequence, earlier proposals to make better use of digital measures to manage the pandemic became more widely discussed (Budd et al., 2020; Ting et al., 2020). In an influential epidemiological modelling study published at the end of March 2020 Ferretti et al. (2020) suggested that sufficiently capable and widely used digital contact tracing apps could dramatically reduce the need for more restrictive containment measures. This proposal gained wide traction in the public debate and among policy-makers, which Figure 1 illustrates with the number of internet searches for related terms. Over the course of spring and summer 2020, digital contact tracing became the poster child of the new class of digital public health interventions.

As digital contact tracing apps were being launched over spring and summer 2020, it became increasingly clear that participation rates lacked behind expectations and behind of what was necessary to reach the full technological potential. As far as adoption rates were being published by the respective government agencies and private initiatives, adoption curves relatively quickly levelled off, as illustrated in Figure 2. Many aspects of the public debate that ensued had little to do with the specifics of digital contact tracing but with digital public health interventions in general: Should participation in such interventions be made mandatory? How to ensure data protection? Should users be nudged towards using interventions, such

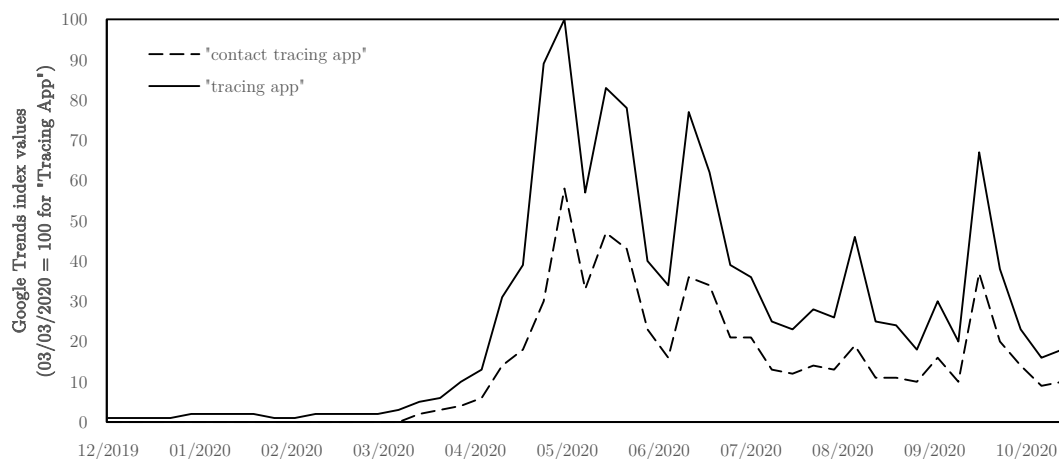


Figure 1: Google Trends (2020) indices for search terms 'contact tracing app' and 'tracing app'

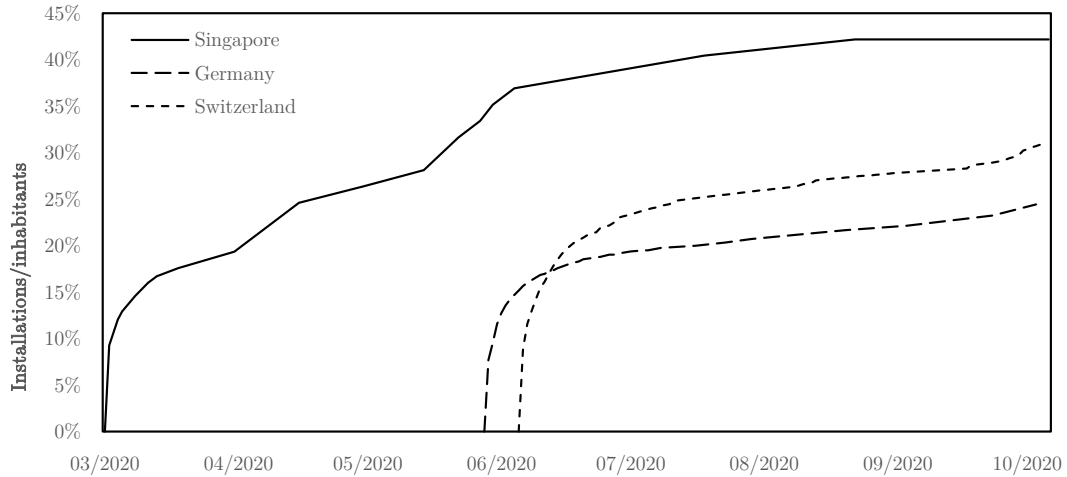


Figure 2: Adoption of digital contact tracing apps in Singapore, Germany and Switzerland

Singapore's TraceTogether app was launched on March 20, 2020. Germany's Corona-Warn-App was launched on June 16, 2020. Switzerland's SwissCovid app was launched on June 25, 2020. The cumulated number of downloads until a respective date was divided by the total number of inhabitants in the respective country as of June 30, 2020 (Bundesamt für Statistik (BFS), 2020a; Statistisches Bundesamt (Destatis), 2020; Department of Statistics Singapore, 2020). For Switzerland, the number of app downloads is frequently published by the Bundesamt für Statistik (BFS) (2020b). For Germany, the cumulated number of downloads is irregularly published by the German Robert Koch-Institut (RKI) (2020). For Singapore, the cumulated number of downloads is irregularly updated on the app's website (Government of Singapore, 2020), which we reconstructed with the Internet Archive's Wayback Machine. The number of downloads does not correspond to the number of active users, since users could have uninstalled the app again or could have turned off Bluetooth.

as by installing mobile apps by default? Should incentives for adoption be put in place or would they crowd out intrinsic motivation? All these questions similarly concern other DPHIs, such as using smart watch data or electronic health records to monitor and manage immediate or more slowly moving public health crises.

In this paper we address the question of how the participation in digital contact tracing and other digital public health interventions could be fostered. We use the term ‘participation’ as an umbrella term for both ‘adoption’, i.e. the first acceptance of the new intervention, and ‘usage’, i.e. the active or passive use after adoption. We proceed as follows: First, we introduce the argument that public health is a public good and how contributions to the public good can be encouraged through different types of interventions. Second, we comprehensively review the literature of economics and – if germane – other fields relevant to fostering participation in digital public health interventions. Third, we provide a detailed overview over digital contact tracing as a digital public health intervention. Fourth, we deduce policy recommendations on how to reach wider participation in digital contact tracing. Lastly, we provide recommendations for further research and encouragement to conduct research on measures to increase participation in digital public health interventions.

2. Public health as a public good

Beaglehole et al. (2004) define public health as concerted efforts to maintain desirable health outcomes of the general population or make positive and sustainable changes to undesirable ones. The term describes both an interdisciplinary research field and a policy goal. Public health interventions are means to achieve this goal. Multiple actors like the health care and education system, government agencies, the media and the general public are involved in those actions (Turnock, 2016, pp. 13-14). The achievement of the goal of public health can be measured via indicators of population-wide health outcomes, such as life expectancy or the prevalence of certain diseases (Turnock, 2016, p. 16).

Public health has the two defining characteristics of public goods (Samuelson, 1954). First, it is non-excludable, meaning that everyone within a community profits from the benefits of good public health (Siegal et al., 2009). For instance, the benefits of herd immunity through vaccinations or lower levels of pollution in potable water due to environmental regulation are usually available to all members of a community and cannot be restricted to a certain group. Second, public health is often characterized by non-rivalry in consumption. Increasing the number of people benefiting from an already existing good does not lead to additional costs of production of that good and does not reduce other individuals' utility from consumption (Feachem & Medlin, 2002). For instance, the costs of achieving herd immunity do not increase when an additional individual benefits from it. This public good nature implies that an individual's efforts to contribute to public health, such as getting vaccinated or avoiding to smoke in the presence of others, unfold positive externalities while non-participation can lead to negative externalities (Elliott & Golub, 2019). In a globalized world, public health even becomes a global public good with non-excludability and non-rivalry not being restricted to the population of only one country or a group of countries. This particularly concerns easily transmittable diseases such as COVID-19, which do not stop at country borders (Feachem & Medlin, 2002).

3. Traditional and digital public health interventions

With public health having characteristics of a public good, public health interventions can be thought of as practical means to implement public good provision. A public health intervention is a bundle of actions aiming at a common goal of ameliorating or maintaining an aspect of population-wide health. These interventions have to be differentiated from clinical interventions, which attempt to improve health at the individual level (Rychetnik et al., 2002). From a technological perspective, one can subdivide public health interventions into two groups: traditional public health interventions (TPHIs) relying only on manual activities and analogous technologies as opposed to digital public health interventions (DPHIs) which are based on or delivered via digital technology like smartphones or the internet (Murray et al., 2016).

3.1. Traditional public health interventions

Traditional public health interventions contribute to improvements in population health but also face many challenges. Prominent examples of TPHIs which are associated with large-scale successes in the field in past decades are vaccination campaigns. They often have the goal of achieving herd immunity for infectious diseases, such as measles or poliomyelitis (Mah et al., 2011). Other common interventions include monitoring food security, environmental hazards and health system quality, infectious disease surveillance and management of disease outbreaks, or education campaigns (e.g. aiming at increasing seat belts usage or promoting workplace safety). More generally, interventions are usually implemented as some form of preventive measure, education campaign, monitoring activity or regulation (Turnock, 2016, pp. 16-17, 27).

Many traditional public health interventions share common challenges. First, their scalability is often limited. Second, rolling out TPHIs at most times requires strong institutions, such as health authorities. Both challenges particularly disadvantage developing countries, which are often in high need for public health interventions but frequently lack the resources and infrastructure to implement them. At the same time, resources and infrastructure also vary within a developing country. For instance, remote areas are difficult to reach, which makes interventions that require physical presence particularly difficult to implement (Mehl & Labrique, 2014). Third, many public health interventions require frequent or even permanent implementation, which is difficult to achieve with TPHIs (Bennett & Glasgow, 2009). For instance, a one-time education campaign might not be suited to bring about sustained behavioral change in the targeted individuals. Fourth, social dynamics around interventions can become pretty complex. For instance, when participation in an intervention is observable to others, it could lead to stigmatization, as has been observed with HIV testing (Young et al., 2009).

3.2. Digital public health interventions

Digital public health interventions have the potential to alleviate some of the challenges traditional public health interventions face. For instance, public health interventions can build on communication channels such as internet websites, social media and smartphone applications to individually tailor messages and education program in order to support health behavior changes and communicate warnings and health advice. These channels also enable symptoms to be reported for disease control and prediction or to remind individuals of preventive examinations (Bennett & Glasgow, 2009; Budd et al., 2020; Aiello et al., 2020). Interventions like the monitoring of blood pressure via a smartphone-integrated sensor (Chandrasekhar et al., 2018) or the continued screening for atrial fibrillation via a smartwatch based on machine learning algorithms (Perez et al., 2019) could be made possible by collective data contributions. Donations to digital datasets also form the base for the development of precision medicine (Kohane, 2015). As mentioned previously, the SARS-CoV-2 pandemic seems to have accelerated the integration of digital

technologies in public health, with digital contact tracing being a particularly promising technology (Ferretti et al., 2020). Those DPHIs often require not only support from institutions but also individual participation of a larger share of the population in order to be effective.

An appealing feature of most DPHIs is their good scalability and their complementarity to TPHIs. Low operating and marginal costs after the first introduction, reduced human resource needs and the ease of digital data transmission facilitate access by a large share of the population – even in remote areas – within short time (Bennett & Glasgow, 2009). DPHIs have the potential to act as complements to TPHIs (Mehl & Labrique, 2014). For instance, sending reminders or enabling registration via smartphone apps or e-mail for a TPHI like a vaccination campaign could increase participation (Milkman et al., 2011).

Furthermore, DPHIs have several advantages that might lead to increased reach and effectiveness compared to TPHIs. First, digital technology could increase the participation in certain interventions by ensuring anonymity for the participants and thereby reducing the risk of stigmatization (Andriesen et al., 2017). Second, DPHIs that are individually tailored and delivered via portable devices which people use in their daily lives can induce more sustained health behavior changes and lower intervention drop-out rates through the frequent interaction with targeted individuals. The potential to generate peer support in online interventions might also be helpful to this end (Bennett & Glasgow, 2009). Third, since digital interventions can be rolled out in a decentralized manner without government support, they present an opportunity to support developing countries with weak institutions from abroad (Mehl & Labrique, 2014). Fourth, DPHIs can profit from the analysis of real-time data – both related and not related to health – in order to identify behavioral patterns that have not been observable before (Aiello et al., 2020).

However, the use of digital technologies in the realm of public health is also associated with new challenges. Before the implementation of a DPHI, its development can have high costs (Bennett & Glasgow, 2009). The development and implementation process further might require public-private partnerships and needs to consider aspects of technology compatibility (Osman et al., 2020). The technology stacks of DPHIs usually require suitable infrastructure as well as wide-spread access and digital literacy of the population and the public health workforce (Budd et al., 2020). During the implementation of a DPHI, the digital collection and processing of data raises concerns over privacy issues and patterns of discrimination in algorithmic decision making (Price & Cohen, 2019). Regarding the aspect of information provision, DPHIs could be vulnerable to the spread of false information and the misinterpretation of accurate information due to more decentralized approaches and the absence of a tight monitoring (McNamee et al., 2016). Furthermore, the anonymity and sometimes low intensity of DPHIs has also been associated with high attrition rates (Bennett & Glasgow, 2009). Finally, after rollout of a DPHI, its effectiveness might change with the rapidly changing technology landscape (Budd et al., 2020).

4. Determinants of the decision to participate in digital public health interventions

The decision to participate in DPHIs is shaped by the perceived costs and benefits. A rational individual's decision is driven by weighing the private costs of DPHI participation, such as monetary costs, effort, switching costs, risk of privacy invasion, against the private benefits, such as improvements in own health outcomes or the desirable feeling of doing good. An individual will maximize its own utility and decide in favor of the intervention if the benefits outweigh the costs. However, an individual's cost-benefit analysis does not necessarily reflect the true costs and benefits, since individuals often lack perfect information and might base their judgements on misperceptions (Nyhan, 2020). Furthermore, rationality can be bounded and cognitive and behavioral biases can affect decision-making (Siegal et al., 2009; Thaler, 2018).

The decision to participate in a public health intervention will also usually be made within a social network, which might alter an individual's perceived as well as actual costs and benefits from participation. This is especially true for DPHIs that often require the participation of a large number of individuals within a community. The presence of other individuals can affect the cost-benefit-analysis in multiple ways. First, a participation decision might pose costs (negative externalities) or benefits (positive externalities) to others. In some circumstances, these externalities might be considered in individual decision-making, as for instance with altruistic motives (Anderson et al., 1998). In other cases, they might not be considered, possibly leading to suboptimal social welfare outcomes (Andreoni, 1995a). Second, the participation decision of other individuals could also directly or indirectly change an individual's utility from participation. Such network effects are present if an individual's utility from adopting and using a DPHI increases with the number of other adopters. This can be most prominently observed for mobile applications with the purpose of enabling communication between individuals using compatible technology (Rohlf, 1974; Bonardi et al., 2020). Third, an individual might consider how others view her participation decision in the context of reputational concerns or social norms (Daughety & Reinganum, 2010). Fourth, the presence of others within a social network also affects the way how and when an individual becomes aware of the existence of an intervention and which expectations are formed about the intervention's costs and benefits (Banerjee, 1992; Young, 2009).

In the following subsections, we review the literature relevant to the decision to participate in DPHIs in more detail. First, we outline common issues to public good provision, which apply to basically all public health interventions. We focus on the need to solve cooperation issues, the need for trust in the intervention, the need to address misperceptions about the intervention, as well as information avoidance behavior. Second, we outline decision criteria specific to public health interventions, such as the conditionality on the personal and public health situation, the integration of the intervention in the wider health system as well as credence good issues. Third, we review aspects of the decision to participate which are specific to the digital realm,

particularly privacy concerns, the digital divide as well as technology design and compatibility. Fourth, we review the relevant innovation diffusion literature.

4.1. Common issues in public good provision

4.1.1. Cooperation

DPHIs face the same “free-riding” problems as other public good provision measures. Due to the characteristics of public health as a public good, individuals are able to fully benefit from good public health without incurring any costs. They cannot be hindered to do this even if they did not participate in the intervention. Even though cooperation would be mutually beneficial, it does not occur or cannot be sustained due to individual incentives to maximize private utility by not contributing without considering public benefits (Fairfield & Engel, 2015; Frischmann et al., 2019). This would suggest high hurdles to rolling out DPHIs. Even small (perceived) costs of participation might hinder individuals’ adoption, if they are able to free-ride on the non-excludable and non-rivalrous benefits resulting from the intervention.

However, people have often been found to contribute more to the public good than one would expect based on the assumptions of neoclassical economic theory (Andreoni, 1995a; Fischbacher & Gächter, 2010). For instance, Andreoni (1995a) conducts a public-goods experiment where a Pareto optimal outcome would result when every participant contributes her whole endowment but contributing nothing is the dominant strategy for a rational self-interested individual. He finds that across ten rounds of this game the average contributions are 44 percent of endowments and on average only 28 percent of subjects per round free-ride. Even though cooperation has been claimed to be especially difficult to achieve with increasing group size due to the low marginal significance of individual contributions, experiments show that individual public good contributions within groups of up to 100 participants are of similar size compared to those of smaller groups (Weimann et al., 2019). Besides experimental evidence, observational studies confirm that public good provision via private contributions does not necessarily fail. A large share of US-Americans is involved in donations every year and a significant number of people donate blood without receiving monetary rewards (DellaVigna et al., 2012; Meyer & Tripodi, 2018).

A common explanation for these findings of cooperation in public good provision is that individuals do not only care about their direct benefits from consuming the public good but that also intrinsic motivations, such as concerns about one’s self-image and others’ wellbeing, and concerns about one’s reputation enter into an individual’s utility function (Bénabou & Tirole, 2006). The warm glow of giving as described by Andreoni (1990) might increase the marginal private benefit from contributing to the public good since an individual enjoys the act of giving. Furthermore, an individual might be motivated by purely altruistic motives meaning that the positive outcomes of others directly affect her utility function in a positive way (Anderson et al., 1998). A preference for reciprocity, meaning that utility-

maximizing behavior is restricted in a way that an individual responds to the contributions of others by contributing (and punishes non-contribution by not contributing), might also at least partially explain cooperative behavior in public goods settings (Fehr & Gächter, 2000a; Croson, 2007).

Indeed, intrinsic motives and reputational concerns have been found to play a role in experiments and real-world settings. Andreoni (1995b) finds experimental evidence that people are significantly more motivated to cooperate in public good provision when there is a prospect of imposing a positive externality on others than when there is a prospect to avoid a negative externality. Frey & Meier (2004) and Fischbacher & Gächter (2010) present experimental evidence that preferences for public good contribution are distributed heterogeneously across individuals. A large share of people contributes conditional on believing that others also contribute, suggesting some form of – at least imperfectly – reciprocal behavior. Evidence from Israel (Wells et al., 2020) suggests that prosocial preferences like altruism played a role in parents’ decision to have their children participate in a polio vaccination campaign that mainly involved public and not private benefits. Campos-Mercade et al. (2020) make use of representative Swedish survey data and show that social preferences are positively associated with contributing to the public good of disease control during the SARS-CoV-2 pandemic by adhering to public health recommendations like social distancing. Similarly, the positive effect of reputational concerns and social pressure on individual’s willingness to donate is confirmed by experiments by Ariely et al. (2009) and DellaVigna et al. (2012). Rogers et al. (2016) find that the perceived observability of their action has a positive impact on the decision to vote among more than 770,000 US citizens.

Even though empirical evidence suggests that cooperation regarding DPHIs will occur in some form, it also suggests that it will not occur at a Pareto-optimal level as, for instance, a public-goods experiment by Andreoni (1995a) suggests. Additionally, public good contributions might decrease over time so that while cooperation in the first adoption of a DPHI could be achieved it might be more difficult to ensure sustainable usage (Fischbacher & Gächter, 2010). This can be explained, among others, by individuals getting accustomed to the benefits of the public good and ignoring the need for continued cooperation to maintain those benefits (Siegal et al., 2009). As Fischbacher & Gächter (2010) point out, it could well be that people tend to contribute less than their neighbors so that cooperation breaks down in the long run. As illustrated by Herrmann et al. (2008), there might also be a tendency to punish those who voluntarily contribute to the public good that could provoke cooperation failure. They show that this might be associated with a weak institutional framework so that sustainable DPHI participation might be especially difficult to establish in many developing countries.

4.1.2. Trust

The adoption of DPHIs also depends on an individual’s trust in other individuals, institutions, science, and technology. One can generally define trust as a person’s willingness to put own – material or immaterial – resources under the control

of another party with the expectation that this act will be beneficial for the trusting person but without any legal guarantee that this expectation will be met by the entrusted party (Fehr, 2009). From a psychological perspective, trust is often described as a heuristic which facilitates complex decision-making processes in situations which are characterized by uncertainty, such as when an individual lacks expertise in a topic in question (Liu et al., 2019). Survey evidence suggests considerable heterogeneity in levels of trust across countries, regions and demographic groups (Algan & Cahuc, 2013). According to Fehr (2009), trust is determined by risk preferences, social preferences (e.g. betrayal aversion or altruism) and beliefs or perceptions about other individuals' trustworthiness. While risk and social preferences are mostly, at least in the short run, exogenous, the beliefs about the trustworthiness of other people are endogenous. They are shaped by the past experiences an individual has had and the type and stability of formal and informal institutions like civil liberties or the rule of law.

The prevailing level of trust within the target population could affect the participation in DPHIs in several ways. First, higher trust in others might increase the willingness to cooperate in public good provision since it leads to the expectation of reciprocal behavior by others and thereby increases the expected benefits from participation (Gächter et al., 2004). Second, trust towards scientists, the media, the government and public health authorities can affect whether people perceive the DPHI as necessary and efficient (Cummings, 2014). It influences the formation of expectations about the private and public benefits of the intervention can thereby increase an individual's self-interest and altruistic motivation to participate. Trust in the parties involved in implementing DPHIs could also decrease the perceived costs of participation when it reduces concerns about aspects like privacy invasion (Vaithianathan et al., 2020). Third, trust in the technology on which the DPHI is based can reduce the perceived costs of adoption (Eiser et al., 2002).

Empirical evidence on the role of trust in public good contributions suggests that it might be of importance for fostering participation in DPHIs. Gächter et al. (2004) find that the correlation between socioeconomic characteristics and cooperation behavior in public-goods games is mainly driven by how an individual's socioeconomic background shapes trust attitudes. Trust is in turn positively correlated with the willingness to contribute. A variety of empirical studies emphasize the importance of trust in public health settings (Weerd et al., 2011; Blair et al., 2017). More recent evidence comes from the analysis of behavior during the SARS-CoV-2 pandemic. Bargain & Aminjonov (2020) use surveys on political trust across European regions and data on regional mobility patterns during the outbreak of the pandemic in Europe. They find that higher levels of trust in political authorities are associated with higher compliance to public health measures such as lockdowns and social distancing orders. They observe that increasing the stringency of pandemic control measures is more efficient in regions with high political trust. These results might be driven by individuals expecting higher personal and societal benefits from compliance when they trust authorities that the measures are necessary and efficient. Brodeur et al. (2020) find similar results for the US. They show that the effect of trust on compliance seems to be driven by trust in the media. In a related study,

Borgonovi & Andrieu (2020) finds that people in US counties with a high degree of “social capital” such as trust in others – even though characterized by larger and denser social networks – reduce mobility more in response to the rise of COVID-19 even before official government measures mandate social distancing.

Not only trust in others but also trust received by others might matter for the decision to participate in DPHIs. Trust has been suggested to be self-reinforcing (Fehr, 2009) and to signal social norms (Sliwka, 2007). An entrusted individual might therefore under certain circumstances be more motivated to participate in a DPHI than an individual which experiences force or monitoring.

4.1.3. Misperceptions

Misperceptions have the potential to significantly affect the assessment of the costs and benefits of a DPHI and thereby to influence participation decisions. Nyhan (2020) defines misperceptions as beliefs in claims which are objectively false or unsupported by evidence. Evidence from experiments (Fischbacher & Gächter, 2010) suggests that beliefs can affect the decision to contribute to public goods. Misperceptions could similarly influence public support for DPHIs. Indeed, recent empirical evidence from lab experiments and observational studies suggests that misperceptions influence the reception of traditional public health interventions to contain the SARS-CoV-2 pandemic. For instance, Akesson et al. (2020) observe in lab experiments that beliefs on the infectiousness of the virus can be miscalibrated and can influence the willingness to take social distancing measures. Similarly, Allcott et al. (2020) and Simonov et al. (2020) find in observational studies that compliance with public health policy measures shows partisan differences and that news reports contradicting recommendations by public health authorities reduce social distancing compliance. The importance of communication, expectation and belief formation is also stressed by Briscese et al. (2020), which study the effect of public health policy announcements on social distancing compliance. These studies confirm evidence on the importance of beliefs in public health interventions more generally. For instance, beliefs which associate vaccines against measles, mumps and rubella with the occurrence of autism – even though not based on systematic evidence and contested by several scientific studies – have had a significant negative impact on vaccination rates, resulting in measles outbreaks in several countries (Swire-Thompson & Lazer, 2020). Social media might foster the adoption of such misperceptions (Johnson et al., 2020).

Misperceptions originate either from an individual’s cognitive processes or from social dynamics influencing these processes. One obvious source of misperceptions are cognitive biases. For instance, Lammers et al. (2020) document an exponential growth bias, a widespread tendency among study participants to incorrectly estimate the growth of SARS-CoV-2 infections in linear terms instead of exponential terms. They link this misperception to participant’s low appreciation of social distancing measures. Similarly, Bavel et al. (2020) suggest that optimism bias – a tendency to view one’s own risk for being negatively affected to be lower than that of others – can result in carelessness in protecting oneself against infections. Besides biases,

misperceptions can also result from the application of common heuristics. One such heuristic might be, for instance, that events with particularly serious consequences also need to have a cause that is proportionately large (Bavel et al., 2020). This makes conspiracy theories appealing to explain terrorist attacks or large-scale public health threats. Another heuristic, the so-called majority illusion, can lead individuals to assume that the beliefs held by their close social environment are representative of the beliefs within the general population (Zhang & Centola, 2019). An even simpler heuristic is, that individuals might assume that information coming from sources they trust is accurate without further analyzing or questioning it (Nyhan, 2020). The extent to which these biases and heuristics as well as other origins of an individual’s misperceptions matter in practice is an active area of research.

The social dynamics leading to misperceptions and to their wider spread are also a largely open area of research. The most relevant active line of research focuses on the spread of false information, which might lead to misperceptions. The spreading of false information can be intentional, e.g. in order to gain or keep political power or economic profit, or unintentional or even well-intended. Generally, information diffusion requires both information provision and information search and consumption. Information spreads either directly via large broadcasts, such as news media, or through word-of-mouth within a social network in the form of information cascades. The internet plays an important role in the information flow concerning health issues² and potentially also for the spread of false information, which might lead to factually false beliefs. Recent research has particularly focused on online social networks. Vosoughi et al. (2018) analyze 126,000 stories on Twitter, shared 4.5 million times in total, with regard to the correctness of their content. They find that false information spreads on average faster and farther than correct information, especially when related to politics. They suggest that this finding might be explained by false information being on average more novel and appealing to different emotions than true information, which might encourage sharing. However, Goel et al. (2016) show that large information cascades are generally rare on Twitter. Direct broadcasts from large information sources like media outlets or influential people account for the majority of far-reaching content. Grinberg et al. (2019) report that in a sample of more than 16,000 Twitter accounts only 0.1 percent of the accounts were responsible for about 80 percent of the shares from media sources associated with systematic false information. Theoretical models on information diffusion show that the dynamics of the spread of information strongly depends on the topology of the network (Kreindler & Young, 2014). It is therefore difficult to generalize from one online social network to another. However, this first empirical evidence suggests, that understanding and making use of the dynamics of information diffusion are a central building block to avoiding misperceptions about public health interventions.

² In 2012, 72 percent of adult US-Americans reported that they had searched online for health-related information within the past year (Fox & Duggan, 2013). This will probably have increased since then. Indeed, during the outbreak of the SARS-CoV-2 pandemic, reports of the first case of an infection in an US state were on average associated with a 36 percent increase in online searches on Google for information about the virus the following day (Bento et al., 2020).

4.1.4. Information avoidance

The decision to participate in DPHIs could be detrimentally affected by peoples' tendency to actively avoid receiving and processing certain information. Evidence collected in the context of health suggests, that even if information is available for free or at relatively low cost, individuals might wish to remain ignorant out of strategic considerations or because they directly derive utility from holding certain beliefs (Golman et al., 2017; Ho et al., 2020). For instance, Oster et al. (2013) document that over a course of ten years out of 1,001 individuals with a 50 percent or higher risk for having inherited Huntington's disease only about 5 percent took a perfectly predictive test before developing symptoms. The authors explain their finding by a model in which individuals receive direct anticipatory utility from beliefs about their future. Weighing the direct utility from preserving optimistic beliefs about the future against the potential future costs of making suboptimal decisions based on these beliefs they might in many cases opt for information avoidance and not get tested. Similarly, Ganguly & Tasoff (2017) show that 5.2 percent of the college students in their sample are willing to forgo 10 US-Dollars in order to not get tested for the herpes virus HSV-1 and even three times as many avoid getting tested for the as more consequential perceived HSV-2 despite financial incentives. This decision can be seen as a refusal to contribute to the public good of infectious disease control. The authors argue that the demand for information declines with decreasing expected consumption utility of the experience the information is about. Ho et al. (2020) observe that preferences for avoiding information are a stable trait within people but not easily predictable by demographic characteristics.

In the context of DPHIs, this could mean that individuals might actively avoid the potential costs that are attached to information provided by DPHIs by not participating. Information provision is at the focus of many DPHIs. Receiving this information can potentially involve considerable hedonic costs when beliefs about one's health status, behavior or risks – that directly enter into the utility function – have to be updated in a negative way. This might be the case, for instance, when an individual learns via digital contact tracing that she is at risk for having contracted a disease or when an app that aims at improving one's health behavior puts the current lifestyle into question.

4.2. Issues specific to public health interventions

4.2.1. Conditionality on the personal and public health situation

An individual's willingness to participate in public health interventions depends on her perception about their relevance. Those perceptions are in turn – at least partially – shaped by the current state of public health and the individual health and risk status. To notice a need for action is a prerequisite for an individual to expect benefits from participating in public health interventions. This need for action becomes obvious when individual and public health outcomes are at risk, for instance during a pandemic. The expected individual benefits from participating in an

intervention like a vaccination campaign increase with the perceived individual susceptibility to the health threat and the perceived severity of the health threat (Weerd et al. (2011); Engle et al. (2020)). An increasing prevalence of the adverse health outcome (e.g. infections with a transmittable disease) within a society and individual risk factors (e.g. having physical contact with infected individuals) can increase individual's perceived susceptibility. Observing the number of very severe outcomes (e.g. the number of deaths from the disease) and assessing one's individual vulnerability (e.g. based on age or current health status) shapes perceptions about health threat severity. Even when interventions have little private benefits, observing the severity of the threat and others' vulnerability might still alter altruistic individual's benefits from intervention participation.

Confirming this view, several studies find that local case numbers and the share of more vulnerable people are positively correlated with the compliance with public health measures like social distancing during the SARS-CoV-2 pandemic (Engle et al., 2020; Brzezinski et al., 2020). Causality is difficult to assess in these cases, but it seems plausible that a deteriorating public health situation and a high individual vulnerability increase the expected benefits from public health interventions and the support for them. However, Akesson et al. (2020) collect evidence that opposes this view. They observe a fatalism effect in an experiment conducted among more than 3,600 people. This effect refers to the observation that beliefs about higher infectiousness of SARS-CoV-2 are associated with decreasing willingness to comply with measures to contain the spread of the virus. People seem to perceive interventions as not effective due to the high perceived general risk. In terms of a cost-benefits assessment, this decreases their expected benefits from participation.

It is important to note, that the conditionality of participation in public health interventions on the personal and public health situation is based on an individual's perception of the situation and not necessarily on objective facts. This ties into the previous discussion on misperceptions.

4.2.2. Integration of interventions into the wider health system

The integration of DPHIs into the wider health system can raise the individual and public benefits from an intervention and reduce the costs of participation. TPHIs and DPHIs are often implemented as vertical 'stand-alone' interventions that only tackle one specific public health problem and are not viewed within the broader context of the health system. While this might be necessary in some cases - like the immediately needed response to a crisis like a pandemic - a more horizontal approach with the integration into the broader system is in general more efficient - from a supply as well as a demand perspective (Atun et al., 2010; Mehl & Labrique, 2014; Budd et al., 2020). Embedding an intervention into the structures of health system governance, resource planning, communication, clinical care, research and regulation, among others, ensures that resources are allocated smoothly and to those in need and that interventions are monitored and complemented by other measures (Mehl & Labrique, 2014). For instance, aggregated data collected during interventions can

help to improve the health system in other areas and inform research (Gong et al., 2020).

Furthermore, the integration of different interventions can also decrease the costs of participation by increasing convenience and facilitating access. In the context of DPHIs, one public health app might serve multiple purposes, such as public health communication, support of health-related behavioral changes, keeping track of vaccinations and symptoms reporting for infectious diseases. Health insurers could get involved and offer bonus programs for sustainable app usage. Local physicians could raise their client's attention to the app during routine encounters. Adjusting such an app to social norms and cultural values might further increase its acceptance (Arakpogun et al., 2020). While integration of different interventions might significantly reduce the individual and public costs and increase their benefits, it might also raise new issues, for instance, if a badly-received intervention has negative effects on the adoption of other interventions.

4.2.3. Credence good issues

Information asymmetries between providers and the target population are a common issue with public health interventions and can substantially decrease participation. Markets which require expert diagnosis and treatment – like markets for medical goods and services – are often characterized by credence good issues. Only the provider of the good or service can really assess – based on expert knowledge – which treatment and which quality of that treatment a client needs. Whether the provider's choice was reasonable and led to efficient outcomes cannot be observed by the client even after the treatment (Dulleck & Kerschbamer, 2006). Many public health interventions therefore have characteristics of credence goods. For instance, a layman is not able to assess the efficacy of a new vaccine in providing him with immunity as long as he does not get infected with the respective disease. Similarly, users of digital contact tracing applications cannot directly observe whether they really receive warnings on the basis of a reasonable risk of infection nor can they observe whether their data is potentially used for purposes besides public health (Vaithianathan et al., 2020). In terms of an individual's cost-benefit calculation, information asymmetries related to public health interventions can lead to increased perceived private risks and costs and decreased perceived private and public benefits and can thereby reduce participation rates.

Whether worries about exploitation are justified obviously depends on the implementation of a particular public health intervention. Most of the times, public health interventions should not involve strong financial incentives for fraud. However, potential participants might still be worried about other aspects like data collection and government surveillance that could motivate interventions (Vaithianathan et al., 2020). False information could play a role in reinforcing those worries (Bavel et al., 2020). The credence good character of DPHIs might especially raise the perceived costs of those with a low socioeconomic status as they have been found to be on average more often exploited in credence good situations and therefore might be particularly suspicious (Gottschalk et al., 2020).

In order to alleviate such worries, measures to build trust, transparency and accountability should be part of the implementation of public health interventions. This is easier to achieve if the general trust in science, public health authorities and experts is high, such that individuals trust the authorities' and experts' judgements in situations where they cannot assess the value of an intervention themselves (Cummings, 2014). Liability and accountability of experts for their actions has been found to increase efficiency in credence good situations, especially when the risk of undertreatment is present (Dulleck et al., 2011). Transparency and a comprehensible scientific evaluation of interventions can also reduce uncertainty and perceived risks and thereby increase the willingness to participate in interventions (Vaithianathan et al., 2020).

4.3. Issues specific to the digital realm

4.3.1. Privacy concerns

Many DPHIs rely on personal data in order to improve the health system and collective health outcomes³, which often raises privacy concerns among potential participants. The revelation of personal health data to other parties can involve risks and costs for individuals like the discrimination from one's social contacts, (potential) employers or health insurers. Firms can use personal data for price discrimination and targeted advertising and criminals can use it for blackmailing and identity theft (Acquisti et al., 2016). Being aware of the unintended disclosure of information to others can also result in anxiety and mental distress and, even without significant consequences, the loss of privacy involves costs in itself (Price & Cohen, 2019). These concerns are reinforced by reports about data leaks and opportunities to identify people in datasets that were deemed as anonymous. This is facilitated by advances in techniques like machine learning and the growing possibility of combining different easily accessible datasets in order to re-identify certain individuals within them (Ohm, 2009). Rocher et al. (2019) estimate that based on 15 demographic characteristics 99.98% of the US-American population could be re-identified in datasets deemed to be anonymous. This finding puts into question traditional techniques of de-identification. Even data that is assumed to be safe from re-identification at present might not remain safe in the future with technological advancements and the availability of complementary datasets.

Decisions over the level of privacy always involve a trade-off between the costs and risks of sharing personal data and the associated benefits. On the one hand, in the context of public health, where personal data can contribute to research or

³ For example, the idea of storing a patient's comprehensive health-related information in electronic medical records (EMRs) to make it easily accessible and transparent to all involved parties promises great efficiency increases and improvements in the safety of medical treatments (Acquisti et al., 2016). Biobanks use big datasets of matched phenotypic and genotypic information of individuals in order to analyze patterns in the occurrence of certain diseases and the susceptibility to treatment methods. They thereby contribute to the development of precision medicine (Kohane & Altman, 2005). Observations of online search patterns have been used to predict influenza outbreaks and digital contact tracing is proposed to control the current Sars-CoV-2 pandemic (Budd et al., 2020).

infectious disease control and thereby to improvements in collective health outcomes, privacy is weighed against a public good (Buzzell, 2020). On the other hand, as pointed out by Fairfield & Engel (2015), privacy itself can be viewed as a public good. The disclosure of personal information does not only involve private costs but also exerts negative externalities on others. One’s personal information could also reveal information about people associated to him (like the health risks of family members based on a genetic predisposition). And in a broader context each personal information added to a dataset increases the opportunities to identify patterns in data and potentially discriminate based on these patterns. Privacy is therefore to some extent non-excludable and non-rivalrous in consumption. This also applies to general standards for data protection. This turns the participation decision in DPHIs into the social choice between two public goods. Abowd & Schmutte (2019) provide an economic model for this choice, according to which the optimal level of privacy protection is chosen where the marginal social benefits equal the marginal social costs of privacy protection in terms of lower data accuracy and representativeness. DPHIs need to address this tradeoff in order to maximize participation in such interventions.

Stated and revealed preferences for privacy are oftentimes strongly at odds. In general, stated preferences for privacy and the protection of personal data are strong (Acquisti et al., 2016). This also becomes visible with regard to digital contact tracing during the current SARS-CoV-2 pandemic. For example, Altmann et al. (2020) document that privacy concerns are the prevailing motive for a decision not to participate in digital contact tracing. However, evidence from real world observations is often at odds with these stated preferences for privacy. For instance, participants in an experiment conducted by Savage & Waldmann (2015) are only willing to pay 4.05 US-Dollar for a mobile app to hinder it from accessing their contacts and only 1.19 US-Dollar to prevent access to their location data. Similarly, Athey et al. (2017) who find in an experiment among students, that even a small incentive like a pizza significantly increases the probability that students would share their friends’ contact data. The difference between strong stated preferences for privacy and often relatively weak revealed preferences has been described as the “privacy paradox”.

Acquisti et al. (2015) suggest that the privacy paradox might be explained by the uncertainty, context dependence and the potential for malleability involved in decisions over privacy protection. First, privacy decisions often have to be made in a context of significant uncertainty. Individuals remain uncertain about whether their data is collected, which data is collected, by whom and for which purposes. This uncertainty is accompanied by uncertainty about one’s own privacy preferences. People express strong preferences for privacy but in concrete situations often seem to be unsure about their real valuation for it. Second, privacy behavior seems to be highly context-dependent. Preferences stated about general attitudes and the concrete behavior in a certain situation do not need to be closely associated (Acquisti et al., 2016). Even emotions regarding one’s physical environment might shape it. Third, privacy behavior is found to often be easily malleable, for instance, by changing decision frames or changing the ordering and default of options. False information might play an especially important role in this context. This malleability

also emphasizes the context-dependence and uncertainty associated with privacy decisions (Acquisti et al., 2015).

Experimental evidence suggests that people’s decisions in the realm of privacy cannot be explained by a purely rational cost-benefit calculus. For instance, Acquisti et al. (2013) document the context-dependence and inconsistency of privacy decisions by showing that people are more willing to exchange their personal data for money when they thought that it was not protected by default opposed to when they assumed it to already be protected. They also find evidence for the malleability of privacy decisions, with the order of decision choices influencing privacy choices, a result confirmed by Athey et al. (2017). Experimental evidence by Marreiros et al. (2017) points to people’s uncertainty about their own privacy preferences by showing that even information about positive changes to a company’s privacy policy reduces the willingness to disclose personal data. This is interpreted as evidence for people’s attention being drawn to the topic of privacy by making them think about it and thereby reminding them of their preferences. This result is in contrast to the finding by Athey et al. (2017) who document that even irrelevant positive information about data protection increases the willingness to share data. An experiment documented by Adjerd et al. (2018) highlights that people’s hypothetical privacy behavior – as stated in surveys – is strongly influenced by the objective privacy risk while in actual decisions behavioral factors like reference dependence (e.g. dependence on the privacy settings in the period before) play a more central role.

These results demonstrate that general concerns over privacy do not necessarily need to translate into low participation in DPHIs as decisions over privacy strongly depend on the context and the uncertainty faced. Trust might play an important role. On the one hand, a convincing privacy-preserving design of a DPHI can build trust in the implementing institutions as it signals benevolence and transparency (Mello & Wang, 2020). It thereby influences the future beliefs consumers have about the institution which might increase voluntary participation in associated interventions. On the other hand, trust in institutions might be a prerequisite to overcome privacy concerns. People often face uncertainty about whether DPHIs only collect and use data as they claim and whether they protect the level of privacy that people demand. Trust is needed in this situation of information asymmetry between DPHI implementers and adopters (Vaithianathan et al., 2020). Low trust in institutions (e.g. due to concerns over governmental surveillance) then poses a barrier to DPHI adoption.

While privacy is an issue that policy-makers have to target in order to increase DPHI adoption, reducing privacy might also be a policy tool to foster participation in public good provision. Daughtey & Reinganum (2010) and Ali & Bénabou (2020) argue that decreased privacy and increased observability of individual actions involves social costs but also increases individual contributions to the public good due to reputational concerns.

4.3.2. Digital divide

The large-scale and broad participation in DPHIs is threatened by significant heterogeneity across countries and across socioeconomic and demographic groups within countries in access and ability to use the technologies DPHIs are based on. Many low- and middle- income countries still have significantly lower per capita rates of ownership and usage of digital technologies and also lack the necessary infrastructure compared to wealthy countries (Arakpogun et al., 2020). Furthermore, even within developed countries, groups with lower socioeconomic status and of older age have been found to have on average less access to digital technologies and lower digital literacy (Aiello et al., 2020; Blom et al., 2020). For instance, in 2017, 13 percent of the population of the European Union had never used the internet. In Romania, Greece and Bulgaria this share was even higher than 25 percent (European Commission, 2018). In the United Kingdom, less than half of the citizens older than 65 own a smartphone (Osman et al., 2020). Access to the respective technologies and the skills to use them are of course prerequisites for DPHI participation before other considerations like those about costs and benefits come into play.

Low participation rates of certain groups due to the digital divide impose costs on those groups and the general public (Kontos et al., 2014; Budd et al., 2020). Limited access to important public health measures and underrepresentation in aggregated health data is disadvantageous to the respective individuals and demographic and socioeconomic groups (Mello & Wang, 2020). This is particularly consequential since the groups with low access to digital technologies might be those in special need for public health interventions, such as people of older age (Blom et al., 2020). Furthermore, negative externalities to the general public result from the digital divide when public health interventions require high rates of adoption throughout the whole population to work efficiently (Blom et al., 2020). This stresses that DPHIs should be seen as complements rather than substitutes for TPHIs (Mehl & Labrique, 2014).

4.3.3. Technology design and compatibility

The design and architecture of the technology that a DPHI is based on can have a significant impact on the individual perceived costs of adoption and sustained usage. For instance, the more time a user needs to invest into getting familiar with the DPHI, the higher are her opportunity costs as she might use this time for other purposes. Opportunity costs are also increased when a DPHI poses restrictions on the use of other applications on the same device, for instance, when a mobile application increases battery usage or demands significant storage capacity (Ghose & Han, 2014; Redmiles, 2020). Furthermore, the design of a technology can influence the perceptions of its transparency and privacy features (Trang et al., 2020). However, one needs to consider that the objective burden of using a certain DPHI might be only weakly correlated with the subjective perceived costs, as suggested by Read (2019), who also emphasizes that there might be significant heterogeneity in how different demographic groups perceive the costs of using a technology. Moreover, it should be considered that the requirements regarding the digital literacy of users

and the technology a DPHI runs on can aggravate issues of the digital divide (Loi, 2020).

The degree of compatibility of a DPHI across already existing technological structures determines the associated network effects and thereby participation benefits (Bonardi et al., 2020). For instance, the compatibility of a mobile application across different smartphone operating systems increases the accessibility of the intervention and strengthens network effects, which increase the marginal private and public benefits from participation (Chen et al., 2009).

4.4. Issues specific to innovation diffusion

The rollout of a DPHIs has to be understood as a dynamic innovation diffusion process. Such processes are complex and discussed in the literature of different disciplines. Young (2009) categorizes the dynamics into three approaches to model innovation adoption: In contagion models innovations spreads like epidemics, with agents adopting upon contact with other agents which have already adopted an innovation. In social influence models agents adopt an innovation once sufficiently many other agents have already adopted. And in social learning models agents adopt innovations once they have collected sufficient evidence that an innovation is worth adopting, with the evidence being collected among earlier adopters. Young (2009) shows theoretically, that these different models lead to different adoption curves, which can but need not to be S-shaped as commonly observed (Griliches, 1957).

The potentially complex dynamics of innovation diffusion also occur in the literature on network externalities. The adoption decision of others does not only signal information relevant for learning from others but also directly affects the benefits from adoption via network externalities (Arieli et al., 2020). Since, due to network effects, an individual's benefits from a technology increase in the number of other users, an individual that observes an increasing number of adopters is also more likely to adopt based on her own cost-benefit calculus (Rohlf, 1974). Another form of network externality can arise from the fact that an individual wishes to conform to the behavior or expectations of her social environment. Social norms are standards for social interactions that themselves evolve dynamically through social learning processes. Adhering to social norms can, for instance, signal one's belonging to a certain group or affects an individual's reputation. Not adhering to a social norm may result in different forms of social sanctions (Young, 2015; Arieli et al., 2020). An individual might therefore have strong incentives to adopt an innovation, for instance, to participate in digital contact tracing, when her social environment adopts it and it finally becomes normative to use it (Beidas et al., 2020). In the early phase when there are only few adopters, the lack of strong network effects or social norms favoring the innovation can significantly decelerate the speed of adoption of a beneficial innovation or might even stop it. At later stages those externalities lead to a self-reinforcing effect that speeds up the adoption process of an innovation that has already gained a foothold within a social network (Arieli et al., 2020; Bonardi et al., 2020).

The speed at which innovations spread through a social network depends on a variety of factors like the network topology, the injection points of the innovation, the relative benefits of the innovation compared to the status quo and the noise in individual’s behavior. Young (2011) shows that social networks characterized by closely-intertwined local clusters foster the spread of innovations since innovations can first gain ground within those clusters and then spread further on. Another factor are the individuals through which an innovation first enters a social network. Banerjee et al. (2013) examine the development of the participation in microfinance in Indian villages. They find that the speed of diffusion is positively associated with the centrality of the contacts of a potential adopter. Moreover, as Young (2011) shows, the spread of an innovation is faster the higher the payoff of the innovation is compared to the status quo. Additionally, Young (2011) as well as Kreindler and Young (2014) find that noise in individuals’ decision-making influences diffusion dynamics by randomly introducing experimental adoption, which – if sufficiently high – can overcome initial adoption thresholds.

Empirical evidence collected in the field suggests that addressing and intentionally shaping innovation diffusion processes is important to ensure widespread adoption. For instance, field experiments conducted by Conley & Udry (2010) and Beaman et al. (2018) in the context of the diffusion of agricultural technology in developing countries demonstrate the importance of social learning when people are uncertain about the benefits and costs associated with the adoption of an innovation.

5. Approaches to foster participation in digital public health interventions

In the following sections, we review the literature relevant to fostering participation in DPHIs. First, we outline the tradeoffs with making participation mandatory. Second, we cover issues in providing information. Third, we evaluate explicit incentives and nudges for adoption and usage of DPHIs. Lastly, we discuss how regulation and technology design can support wide-spread participation.

5.1. Mandatory and voluntary participation

Participation in public health interventions can be either voluntary, mandatory or conditionally mandatory. Under a policy of voluntary participation, individuals freely choose to opt in or out of the participation in a public health intervention without any punishment by authorities.

Mandatory participation can arguably lead to high intervention adoption rates but also raises concerns. One example are mandatory vaccination policies. For instance, US-states require children to get vaccinated as a prerequisite for being admitted to public schools (Wynia, 2007; Stewart, 2009). Such policies often require significant monitoring to enforce compliance. Additionally, being mandated to engage in an intervention can lead to negative spillovers to other behaviors related to public health (Bonardi et al., 2020). The mandate might be perceived as a signal of the

authority’s distrust in the people and diminish intrinsic motivation (Gneezy et al., 2011). In general, ethical concerns over the restrictions of civil liberties are an important counterargument (Mello & Wang, 2020).

Conditionally mandatory participation is a less invasive strategy but raises similar ethical and practical concerns. Under this regime, people need to participate in the intervention in order to enter certain places or perform certain activities. For instance, being allowed entrance to public transport might be conditional on proving that one participates in digital contact tracing (Bonardi et al., 2020). This significantly increases the costs of non-participation.

Balancing the costs and benefits of these different regulatory regimes prior to the rollout of a DPHI is inherently difficult. While political decision-makers might retreat to political ideology when making choices among these different regimes, a more fruitful approach would be to experimentally test these different regimes in combination with other measures to foster participation. None of the measures to foster participation is likely to be “silver bullet” leading to high adoption and usage. Rather, the path to widespread participation has to be intentionally designed, with different measures serving as complements or balancing off other measures’ weaknesses.

5.2. Information provision

5.2.1. Communicators and communication channels

Not only the messages but also the messengers matter for successful provision of information on DPHIs. Personalities entrusted by the targeted parts of society could potentially be effective messengers. Due to the credence good characteristics of many DPHIs – lay people cannot assess the need for and efficacy of the measures even after adoption – it is important that those who communicate the benefits of a DPHI are perceived as trustworthy (Vaithianathan et al., 2020; Bavel et al., 2020). Several studies show that higher trust in the government and the authorities who communicate measures is associated with higher levels of compliance with those measures during public health emergencies (Blair et al., 2017; Bargain & Aminjonov, 2020). Trustworthiness depends on past experiences (Fehr, 2009). For instance, it can be affected by whether the person or institution was perceived as independent, without conflict of interest, competent and consistent in its messages and actions in the past (Cummings, 2014). To foster the acceptance for public health messages, people should therefore hold positive beliefs about the expertise, reliability and benevolence of communicators based on prior experiences with them. In the US, trust in scientists and health professionals seems to be significantly higher than trust in the media and the government (Swire-Thompson & Lazer, 2020). Thus, the population there might be more likely to update their beliefs based on communication about a DPHI when this communication is directly linked to public health experts.

First evidence on the efficacy of communication measures during the SARS-CoV-2 pandemic and past vaccination campaigns shows that choosing trustworthy communicators can be helpful to increase participation in public health interventions.

For instance, Allcott et al. (2020) show that diverging messages by political leaders in the US across the political spectrum appears to have shaped beliefs and participation in public health measures. Alatas et al. (2019) conduct an experiment with Indonesian celebrities on Twitter and find evidence of a celebrity endorsement effect. Messages about vaccination campaigns tweeted by celebrities do not only reach more people due to the large number of followers but also because followers are more likely to share such tweets compared to those by peers. Banerjee et al. (2020) find in a randomized controlled trial involving 28 million Indians that sending a text message containing a message by a prominent and trusted person is associated with increased compliance to public health measures during the SARS-CoV-2 pandemic. This effect on behavior does even spill over within communities to those who did not receive such a message.

Digital technologies are an important medium to spread information about DPHIs (Budd et al., 2020). As already pointed out, many people seek health-related information online (Bento et al., 2020). Websites, mobile applications and messengers and social media channels can therefore have a great impact in supporting the diffusion of information about DPHIs. Some DPHIs might even be used to foster the participation in other DPHIs through messaging functionalities. It might also be worthwhile to try to engineer viral distribution of public health information. For instance, referrals to DPHIs could be incentivized.

5.2.2. Design and timing of communication

The information provided should be transparent, ideally based on scientific evidence and avoid conflicting messages (Weerd et al., 2011). This can significantly alter people’s perceived costs and benefits of DPHIs towards a more positive evaluation. Additionally, trust can be built when people update their beliefs about the respective communicators in a positive way. To this end, information provision should not remain a one-way street from providers to participators but those designing and implementing the DPHI should also consider feedback from the respective communities. This provides a form of social licensing and potentially builds up trust in the project (Vaithianathan et al., 2020). However, when trust is a prerequisite for accepting messages, the efficacy even of good communication concepts can be limited in low-trust populations (Blair et al., 2017).

The efficacy of an information also depends on its framing. This is an aspect closely related to nudging. Public health communication often emphasizes the public benefits of an intervention. This can appeal to people’s prosocial motives and make social norms salient and thereby raise perceived benefits (Bonardi et al., 2020). However, as shown by Wells et al. (2020), increasing the comprehension of the prosocial nature of an intervention in a population might not always benefit the intervention, depending on the degree of altruistic preferences in the population and the perceived risks of the intervention. Instead, the correction of misperceptions about the associated risks might be more helpful to ensure success. Many public health interventions also involve significant private benefits. This applies, for instance, to vaccinations against infectious diseases in the absence of herd immunity

or to digital contact tracing. In those cases, it might make sense to also highlight private benefits in order to increase participation rates (Bonardi et al., 2020). Providing a clear understanding of the individual benefits of a DPHI could also reach those who refuse participation out of information avoidance considerations (Oster et al., 2013).

Communication on public health interventions should also be framed in such a way, that it clearly points out the severe consequences that might result from not addressing a public health threat. This can make the private and public benefits of participation more salient. For instance, events and risks are often perceived as more probable if they receive large-scale media coverage. This phenomenon is also referred to as availability heuristic (Siegal et al., 2009). However, if threats are perceived as overwhelming, this might trigger a fatalism effect through which the threat is perceived as so large that interventions are not considered to be effective and the willingness to participate decreases (Akesson et al., 2020). These opposing effects have to be balanced off against each other.

Another aspect of the framing of information is to clarify the trade-offs involved in the adoption of DPHIs. While interventions might involve costs like personal effort or privacy risks, those costs need to be presented in the context of the associated benefits, such as potentially saving lives and protecting the health of parts of the population. One way to illustrate trade-offs is to present evidence on potential counterfactual outcomes (Mello & Wang, 2020). Communicating public health measures also concerns communication on costs of an intervention, which might have ambiguous effects. On the one hand, presenting information on how costs are minimized might deem public health interventions as cost-effective. On the other hand, communicating costs might actually draw people's attention to those costs and increase their concerns, as studies regarding individuals' decisions over privacy reveal (Marreiros et al., 2017).

Besides building trust and properly framing communication on digital public health interventions, the timing of communication should also be carefully chosen. For instance, Bento et al. (2020) show that large events associated with public health threats might only induce a short period of increased attention to information regarding the threat. This suggests that communication on DPHIs needs to be conducted quickly after a public health threat arises.

Lastly, communication on DPHIs has to anticipate that the effects of communication are likely to be heterogeneous. How a message is perceived and reacted to might, for instance, depend on heterogeneous risk preferences, trust towards the communicator or expectations formed prior to receiving the message (Briscese et al., 2020; Fan et al., 2020). Digital technologies can provide a solution to this end by enabling to send people tailored messages based on their observable characteristics (Bennett & Glasgow, 2009).

5.2.3. Addressing misperceptions

The providers of DPHIs also need to address misperceptions and attempt to correct them, for instance, by counteracting the spread of false information.

Experimental evidence collected by Akesson et al. (2020) and Lammers et al. (2020) during the SARS-CoV-2 pandemic suggests, that providing true information has the potential to correct misperceptions. However, this might not always work, especially when false information has been spread intentionally. Nyhan & Reifler (2010) even argue that the correction of misperceptions by evidence-based information can lead to a backfire effect and strengthen beliefs in false claims. This might be, among others, explained by people’s tendency to stick to claims that they are motivated to believe in (Levy, 2017). In his review of the related literature, Nyhan (2020) suggests that the backfire effect is a rather uncommon phenomenon. However, false information could also be countered differently. For instance, sources with verified information could be labeled and fact-checking services can reduce uncertainty when seeking advice. To this end, public authorities could cooperate with entrusted independent scientists, health professionals and fact-checking services.

A more general approach to counter misperceptions about DPHIs is obviously to invest in media, health and digital literacy. Related education campaigns can increase the population’s ability to distinguish false and true claims and to critically question the information encountered online and offline (Swire-Thompson & Lazer, 2020; Nyhan, 2020). Furthermore, the supply side of information leading to misperceptions about DPHIs might be addressed. A field experiment by Nyhan & Reifler (2015) finds that raising politicians’ awareness for being monitored by fact checkers and to the potential reputational consequences of communicating false information can reduce their propensity to make false claims.

5.3. Explicit incentives

5.3.1. Material incentives

Monetary incentives can provide a means to increase cooperation and participation in DPHIs. If an individual faces private costs when contributing to the public good but perceives little private benefits, monetary rewards can compensate for the private costs and thereby increase the willingness to participate. Financial incentives can take different forms, such as direct payments conditional on an individual’s participation in a DPHI as well as fines for free riding. Both positive and negative incentives have been shown to increase cooperation in public good provision under certain circumstances (Fehr & Gächter, 2000b; Kraft-Todd et al., 2015). Material rewards like t-shirts or mugs, or providing free products or medical treatments can similarly be used as incentive devices. For instance, in areas where the digital divide poses significant barriers to large-scale DPHI adoption, providing the technology that the DPHI is based on, such as a smartphone, for free or at lower costs could significantly foster adoption.

The significant costs that material incentives impose on their provider can be justified with the positive externalities they can generate. Strong positive externalities of the participation in an intervention, for instance, due to network effects, can substantiate incentives from a social welfare perspective (Dupas, 2014). In order to decrease the associated costs and increase efficiency, they could also be

strategically targeted at certain individuals instead of all potential participants. Providing incentives to people who adopt an intervention early on or are particularly influential within a social network can convince them of a DPHI. This, in turn, can generate positive spill-over effects on peers and accelerate the diffusion process. Similarly, referral rewards could be another tool to use the existing social network for advertising adoption. Kornish & Li (2010) show that the effect of a referral bonus of a certain height depends on how much the targeted person is concerned about the outcomes of her contacts.

5.3.2. Issues with material incentives

Even though material rewards are an intuitive way to stimulate the participation in DPHIs, their usage can also trigger undesirable effects which decrease their efficiency and can even lead to counterproductive results. One concern is that incentivizing DPHI adoption by material rewards might alter people's expectations when people have reference-dependent preferences (Kőszegi & Rabin, 2006). Their reference point might change such that they expect to also be compensated for participation in the future. This can threaten the sustained usage of a DPHI once the reward is no longer provided and might also exert negative spill-over effects on other public health interventions when the willingness to participate in them without compensation decreases based on past experiences of incentives (Gneezy et al., 2011). Nevertheless, in a field experiment with subsidized health products, Dupas (2014) finds a positive effect of one-time subsidies via stimulated social learning and no negative effect of a changing reference point.

An even bigger class of concerns for using material incentives is, that they might crowd out intrinsic motivation by interacting with individual's prosocial motives and their concerns for their self-image and social reputation. First, the provision of an incentive to participate may contain a negative signal to the respective individual. It might, for instance, be interpreted as a signal that the authority does not trust individuals' own motivation. This might reduce the motivation to participate out of preferences for reciprocity or more generally decrease the utility the individual receives from performing a benevolent task (Gneezy et al., 2011). A similar effect might occur when the incentive is interpreted as a signal that participation in the DPHI is so costly and privately unbeneficial that it needs to be incentivized (Bénabou & Tirole, 2003). Similarly, imposing a fine on free riding could also be interpreted as a signal of how costly free riding is for the society. An individual could then decide to simply pay the 'price' of not contributing and thereby distance from feelings like shame for non-contribution (Kranton, 2019). It should also be considered that the provision of referral bonuses can have adverse effects on social learning when people anticipate that their peer's intrinsic motivation might have been undermined by other incentives and the recommendation might therefore be less credible and contain a weaker quality signal (Sun et al., 2020).

Second, a material incentive can reduce the positive social signal that public good contributions send to those who observe them. Contributions might be perceived as mainly driven by self-interest when incentivized and thereby no longer

serve as a signal that improves others' perceptions of the individual. Therefore, incentives might crowd out the motivation resulting from reputational concerns (Bénabou & Tirole, 2006). Ariely et al. (2009) find in an experiment that the introduction of monetary incentives increases anonymous donations to charity but has no effect on donations which are observable to others.

Third, material incentives may change the frame within which the decision to participate is made. Incentives might prompt individuals to view the decision to participate as an economic transaction in which they maximize private utility instead of a social interaction to which, for instance, preferences for altruism and warm-glow giving apply (Bowles & Polanía-Reyes, 2012). The change from a social to a monetary frame might explain the experimental finding by Gneezy & Rustichini (2000), who show that if compensation is paid, compensation increases are associated with increasing performance of participants. However, those participants who receive a relatively low compensation perform worse than those without compensation. This might be explained by intrinsic motivation applying to the setting with no compensation and low extrinsic motivation replacing intrinsic motivation as soon as a small compensation is paid.

Fourth, receiving material rewards can give individuals a feeling of being monitored and undermine their sense of self-determination. The decision to participate is no longer perceived as being made autonomously which may result in lower utility from taking that decision. Fifth, in the long run, preferences may be endogenously determined and shaped by the environment of an individual. When prosocial behavior is incentivized by material rewards, an individual might update her beliefs about the prevailing social norms and the motivation of the people around her. Conformist motives might then lead an individual to adopt preferences that are more self-interested (Bowles & Polanía-Reyes, 2012).

A more indirect crowding out effect might result from rewards inducing sorting effects, where participants are not the ones who are most intrinsically motivated (Meyer & Tripodi, 2018). While DPHI adoption is boosted in the short run by the incentive, the sustained usage might decline since those who participate in a subsidized intervention are people who are less interested in its success than the people who might have otherwise been attracted. The adverse sorting effects of material rewards have also been observed in the commercial context (Sun et al., 2019). Yet, depending on the expected time-frame of a DPHI, a shorter-term boost of participation induced by the ability of participants to sort into incentive and non-incentive schemes might be helpful for increase the efficacy of certain interventions.

Since material incentives and intrinsic motivation can be substitutes under certain circumstances, policy-makers need to consider that incentives do not only affect individual costs and benefits of participation but also the beliefs and preferences underlying the decision to participate in a DPHI. The relationship between an intervention provider and the target population, the information that incentives signal and the underlying social norms in a society need to be considered. To foster a more complementary character of material incentives and intrinsic motivation, incentives should be accompanied by messages which explain the social and moral frame of participation and the supportive meaning of incentives. Potential

adopters need to understand that their participation is essential to provide the public good and what the benefits associated with that public good are. Additionally, feedback from society, as well as the prevailing local norms and perceptions, need to be considered (Kranton, 2019). For instance, more civic minded societies with high preferences for prosocial behavior and high levels of trust might require lower material incentives than those with a lower level of prosocial preferences (Bowles & Polanía-Reyes, 2012).

Often – but not always – it might be efficient to use a lower level of incentives than the level that would be chosen when not considering the interaction with intrinsic motivation. However, when a certain critical level of participation in a DPHI is needed to ensure that the public good is provided, it can be optimal to choose an even higher level of incentives than a naïve planner to compensate for the relative inefficiency of incentives. This could, for instance, apply when a certain level of vaccination coverage has to be reached to achieve herd immunity. In such cases, the marginal social benefit of participation increases sharply as soon as participation falls under a certain threshold, justifying even very high levels of incentives (Bowles & Hwang, 2008).

5.3.3. Non-material incentives

An alternative to material rewards for participation could be the presentation of awards. Receiving an award can enhance one’s self-image and thereby increase intrinsic motivation. The crowding out effect as with material incentives is less likely since awards are perceived as a gesture of support and not control. Additionally, they can be a favorable social signal to others and thereby appeal to individual’s reputational concerns. From a supply-side perspective, awards are efficient since they do not involve major costs to their provider. However, the provider needs to be able to effectively restrict their supply because their value to an individual decreases with a growing number of the same awards being presented to others. Being short in supply makes awards’ signal of social distinction credible but also limits the scalability of this incentive scheme. Furthermore, awards require trust and acceptance from the recipient towards the supplier. They will not be valued when the providing institution is not perceived as prestigious as might be the case when individuals distrust public institutions (Frey, 2007).

Assessing the causal effect of awards on motivation and performance is relatively difficult. Awards might foster motivation but those who are more motivated are also more likely to receive an award (Frey & Gallus, 2017). Gallus (2017) attempts to overcome this identification issue by conducting a large-scale field experiment where awards are randomly assigned to new contributors on Wikipedia. Even though those awards are purely symbolic and can only be linked to the contributor’s online pseudonym, they have a significant positive effect on the willingness to contribute in the future. Gallus (2017) explains this finding by the fact that awards increase an individual’s self-identification with the online community and signal social status within this community so that they act as a motivating device.

Another explicit non-material incentive can be the creation of social pressure by making individual contributions and also free riding visible to others. Policy-makers might decide to decrease individual privacy of action with regard to the participation in DPHIs and thereby increase the motivation out of reputational concerns. When concerns about how others view one’s behavior directly enter into the utility function, individuals might perceive increased benefits from participation when they know that their actions can be observed. Free riding is then associated with significant costs in the form of being shamed for not contributing (Daughety & Reinganum, 2010; Ali & Bénabou, 2020). However, a policy of decreased privacy also brings about issues of its own. When individuals distort their contribution behavior out of image concerns, this behavior becomes less meaningful to infer the underlying social preferences. This might decelerate the process of the formation of new social norms and the policy and legal change based on those norms (Ali & Bénabou, 2020). Importantly, inducing social pressure might also crowd out intrinsic motivation, for instance, by eroding the trust relationship between the authority and citizens (Gneezy et al., 2011).

5.4. Nudges

5.4.1. Nudges as a policy instrument

Nudges are “features of the choice architecture that influence the decisions people make without changing either objective payoffs or incentives” (Thaler, 2018, p. 1283). Since individuals do not incur any significant costs to avoid them, nudges should not affect the decisions of rational individuals which are fully aware of their preferences and simply weigh the costs and benefits of a decision but should lead to better decisions of individuals which are not fully rational and rely on intuitive thinking or heuristics in their decision-making processes. In the case of DPHIs, non-participation might, for instance, not be driven by the individual costs of participation outweighing the benefits but rather by heuristic decision-making or forgetfulness (Milkman et al., 2011), which might lead to individually and socially suboptimal outcomes. Nudges targeted to address such issues could therefore help to increase participation rates.

There is no clear-cut classification of what counts as a nudge. Changing defaults, promoting commitment strategies, increasing the ease and convenience of certain decisions or changing the framing of a decision are typical examples of nudges. In contrast, the mere provision of information in situations of uncertainty is arguably not a nudge since it would also alter the decisions of fully rational individuals. Similarly, building up social pressure by decreasing privacy of actions can arguably not count as a nudge since decreasing privacy might be seen as some form of force and social pressure might be strong enough to considerably change the choice options available to people (Schubert, 2017).

Nudges are an appealing policy instrument since they are usually associated with low implementation costs, do not require laborious monitoring – as with bans or taxes – and are perceived as less invasive than other measures since they do not restrict individual’s options or alter the costs and benefits of certain decisions

(Bhargava & Loewenstein, 2015; Capraro et al., 2019). Therefore, nudges can be considered to be an instrument for libertarian paternalism, which aims at changing people's behaviors to what is perceived as being in their own best interest, without restricting the freedom of choice. This contrasts with heavy-handed paternalism, which operates with mandates, restrictions and changing economic incentives (e.g. taxes and subsidies) to achieve improvements in what is perceived as the people's own interest. It should, however, be mentioned that nudges in the context of public good provision are often non-paternalistic, meaning that they do not aim to increase every single individual's utility but aim at the welfare of the overall society (Schubert, 2017).

5.4.2. Evidence on the effects of nudges

Nudges have been implemented in many forms, for instance in the areas of health and environmental protection. Some empirical results suggest positive effects of nudging on people's decisions to contribute to public goods. A prominent example of nudging is the change in defaults in participation decisions. If participation is seen as desirable – as in the case of DPHIs, or, in general, in public good provision – policy-makers can make participation the default option such that individuals have to actively opt out in order not to participate. To count as a nudge, of course, no significant barriers or costs should be associated with opting out (Bonardi et al., 2020). Johnson & Goldstein (2003) show for a sample of European countries that the rate of people consenting to organ donation is between 85 and almost 100 percent in countries where this is the default option, whereas the rate is lower than 30 percent in countries where an active opt-in is necessary. This seems to lead to significantly higher organ donation rates in countries with a default choice to opt in. The impact of a default nudge might be explained by several factors. First, people might perceive the default as a recommendation, as a preferable option chosen by the policy-maker or reflecting social norms that guides decision in complex and uncertain contexts (Johnson & Goldstein, 2003). Second, consumers might exhibit inertia and a bias towards the status quo since they prefer to avoid making active decisions that might involve effort and cognitive or emotional costs when trade-offs are faced. Third, people may perceive the default as a reference point. Deviations from this point involve losses due to the associated trade-offs (like the trade-off between contributing to the common good of organ donation and suspicion about the practice of organ donation). Loss aversion – a tendency to weigh losses more than equivalent gains – can then lead people to stick with the default option (Johnson & Goldstein, 2003; Schubert, 2017). Setting a default might be seen as one way of framing a decision.

Other ways of framing, for instance, changing the order of options or presenting a trade-off in terms of losses or gains, can also significantly affect decisions. Martinsson et al. (2019) provide an example in a public goods game. They find that cooperation is significantly higher when contributions are framed as giving to the public good, compared to not taking from the public good. Other experiments confirm the effects of framing (Andreoni, 1995b; Acquisti et al., 2013). Depending on the nature of the framing, the results could possibly be explained by similar factors

like those at play in the case of defaults, for instance, loss aversion and inertia (Acquisti et al., 2013; Michalek & Schwarze, 2020).

Reminders and implementation intention prompts are another class of nudges, which has been shown to work in real-world settings. Yokum et al. (2018) find that sending letters to remind people to get vaccinated against influenza had a significant positive impact on vaccination rates among 228,000 people in a randomized controlled trial. However, relative to informational or motivational letters, they find no additional positive effect of implementation intention prompts, i.e. letters that non-bindingly asked people to write down the date and time when they plan to get the influenza vaccination. This contrasts a finding from a field experiment by Milkman et al. (2011) in which receiving an implementation intention prompt had a significant positive effect on vaccination rates relative to informational reminders. As the authors point out, implementation intention prompts might help people to overcome procrastination and forgetfulness by making concrete plans that link their initial intentions to actions.

Shifting the focus from individual decision-makers to cooperative decision-making, social nudges try to make use of the observation, that many people cooperate conditional on others' cooperation in public goods games (Frey & Meier, 2004). They might therefore be motivated to cooperate when information about the share of other people that cooperate and the amount of their contributions is – in a non-identifiable manner – disclosed, given that others have cooperated to a significant extend (Michalek & Schwarze, 2020). From a theoretical standpoint, it is not trivial that people are conditional contributors. On the one hand, if the main motivation for public good contributions is altruism, own and others' contributions could be substitutes. The more others contribute, the more increases other people's utility from the public good so that the marginal effect of a person's contribution on others' utility, about which she cares, decreases. On the other hand, others' and own contributions can be complements when preferences for reciprocity play a main role, when others' contributions are seen as signaling a social norm to which one wants to conform or when people use simple heuristics that suggest them to imitate others' behavior (Shang & Croson, 2009; Schubert, 2017). Empirical evidence appears to confirm the second view, i.e. people increase public good contributions when they are informed that others contributed and even when others non-bindingly announce that they will contribute (Frey & Meier, 2004; Kessler, 2017). However, it should also be noted that people may tend to contribute at a lower level than the ones they observe (Fischbacher & Gächter, 2010).

Building on conformity motives and prosocial preferences, a policy-maker can also use nudges to make social norms or the general moral aspects of a decision more salient. Capraro et al. (2019) use a simple question to prompt individuals to think about the moral dimension of their actions before they participate in an economic game. They show that this moral nudge significantly increases prosocial and cooperative behavior and that this effect also spills over to other contexts. Barron & Nurminen (2020) give a share of the participants in their public goods game the information that a certain level of contribution is viewed as 'good' or desirable from

a social perspective. Providing such a reference point to individuals has a significant positive effect on their contributions to the public good.

Another way of nudging people towards public good contribution can be to disclose the (negative) consequences of their past behavior or to make those more salient, for instance, by using simplified descriptions and depictions. An experiment by Butler et al. (2020) shows how giving public feedback on past community behavior via a mascot that expresses respective emotions or via simple visualization of the respective data can increase people's prosocial behavior compared to the mere provision of the respective data in a private setting.

5.4.3. Issues with nudges

Not all nudges have the intended effects. In certain contexts, they have been shown to be relatively ineffective or to even have negative side-effects. For instance, Goette & Tripodi (2020) provide blood donors with positive feedback on the use of their past donations in order to increase their intrinsic motivation. Contrary to what might be expected, the authors find that this information has a negative effect on people's future blood donations. This could be explained by moral licensing. People derive utility from positive beliefs about themselves and therefore invest in their identity by behaving prosocial and moral. When they are reminded that they acted morally in the past and update their beliefs such that they are a moral person already, investments in their own identity will pay off less and they might feel less urged to act morally again in the nearer future (Bénabou & Tirole, 2011). Goette & Tripodi (2020) find that attaching an explicit appeal to donate blood again to the feedback can help to overcome the negative consequences of moral licensing but does not induce an overall positive effect of the nudge.

Another issue that has been highlighted is that in some cases nudges and traditional policy tools can act as substitutes since the use of nudges crowds out support for more invasive but also more effective measures. Hagmann et al. (2019) find support for this assumption by conducting several experiments. They document that respondents are less likely to support a carbon tax when they are provided with the alternative of implementing a default nudge aimed at choosing renewable energy supply. Similarly, the support for increasing social security contributions was partially crowded out by the possibility to implement a nudge regarding retirement savings plans. Also in this case, moral licensing might provide an explanation for this finding. People update their beliefs such that they are a moral person when choosing the nudge and do not feel the need to support policies that impose higher costs on them. However, Hagmann et al. (2019) show that such a crowding out effect can be prevented by correcting people's beliefs about the effectiveness of both policy tools before they take the decision.

Furthermore, an often articulated concern is that the use of nudges as policy tools might be unethical. First, paternalism assumes that the policy-maker can figure out what is in an individual's or in the wider society's best interest. However, in many circumstances, it is difficult to assess what maximizes either an individual's or society's utility. Additionally, policy-makers – especially in countries with unstable

or undemocratic institutions – do not always act on behalf of the people (Schubert, 2017; Engelen, 2019).

Second, nudges operate on the basis of people’s cognitive and behavioral biases, often without people noticing the impact of those nudges. This might be perceived as nontransparent and manipulative. Paternalistic and non-paternalistic approaches might be perceived to undermine and disrespect individual’s autonomy (Engelen, 2019). If people feel manipulated, this can backfire by reducing their trust in institutions – a trust that is needed for interventions to be accepted. The destruction of the trust relationship between people and policy-makers can also crowd out intrinsic motivations to participate in public good provision (Gneezy et al., 2011). Reactance – a psychological defense reaction to the perception that one’s freedom is at threat – might even lead to behaviors contrary to what the nudge intended (Bruns et al., 2018).

Third, nudges may affect preference formation, social learning, and policy development processes by manipulating people’s behavior. They might crowd out policies that focus on the structural reasons for suboptimal outcomes and might make people’s behavior less informative for policy-makers to observe changing social norms and preferences (Bhargava & Loewenstein, 2015; Schubert, 2017). Fourth, nudges may have redistributive effects and under some circumstances disproportionately affect those with a lower socioeconomic status (Ghesla et al., 2020).

One way to tackle some of those issues could be by making nudges, their intentions and impacts, more transparent and thereby diminishing concerns over subtle manipulation. For instance, Bruns et al. (2018) show in a laboratory experiment that the positive impact a default nudge has on contributions to the reduction of carbon emissions does not decrease when people are transparently informed about the features of the nudge before making their contribution decision. It should also be considered that different types of nudges vary in the degree of how strongly they change people’s choice architecture and try to guide choices in a certain direction. Simply providing information about the share of other people who contribute might in this regard be perceived as less invasive and questionable than changing defaults, for instance (Patel, 2018).

Another way to address ethical issues with nudges is to provide nudges to reason, as suggested by Levy (2017). These nudges do not aim at exploiting people’s cognitive and behavioral biases but instead try to foster their critical thinking and responsiveness to best evidence. One could, for instance, frame best scientific evidence in a way such that it becomes more salient or have it presented by people who are perceived as credible by the targeted population. This way it becomes easier for this group to question own misperceptions and make responsible and well-informed decisions.

Finally, nudges might be more acceptable if their implementation is guided by ethical principles, for instance, by weighing the costs and the potential benefits of their introduction beforehand by parliament or other representative committees. The use of nudges might, for instance, be easier to justify in situations of a large public health threat. If a reliable mechanism to collectively decide on such justifications is available, using nudges could well be justified even to concerned members of society.

5.5. Regulation

Consistent and transparent regulation can help to build trust in DPHIs and those who provide them and decrease the perceived risks of participation. Policy-makers should consider to bind themselves by clear rules and monitoring when implementing DPHIs (Mello & Wang, 2020; Amit et al., 2020). This helps to ensure and signal to the public that the adoption of DPHIs is in line with the principle of proportionality. Furthermore, such interventions should be appropriate given the targeted public health goal and should be the minimally invasive means to achieve that goal (Ienca & Vayena, 2020). Legal guidelines can prescribe a maximum period of operation for a DPHI with subsequent data deletion when the DPHI is a response to an acute crisis. The scope and purpose of the collected personal data, the institutions having access to that data and the technological approach to data anonymization could be transparently determined within a legal contract. Compliance to such a contract might be monitored by an independent committee constituted by experts, among others, from law and ethics, and representatives of the wider public. This committee might require regular reporting by the providers of DPHIs, conduct data audits and the like (Price & Cohen, 2019; Amit et al., 2020). As a consequence, individual's concerns about the misuse of their data or unconstrained government surveillance might be mitigated which reduces the perceived costs of DPHI participation. To this end it is important to clearly communicate the purpose of regulations and put them into context so that their benefits are recognized and understood by the population.

More generally, a transparent and well-developed legal framework for privacy protection can help to mitigate related concerns. In the context of public health interventions, it appears to be particularly important to have a legal basis for allowing or prohibiting the linking of health-related data with other data sets, to impose significant fines on data misuse, such as the purposeful reidentification of individuals, and to require high standards of data protection (Kohane & Altman, 2005; Ohm, 2009).

Another area where regulation can play a role is the reduction of the spread of false information. Websites associated with systematic false information could be regulated or even banned. Reducing the reach of social media groups that frequently communicate false claims is another possible measure to increase participation in public health interventions such as vaccinations or digital contact tracing. However, such regulations raise substantial concerns over censorship and restrictions of the right to freedom of speech and the freedom of the press. The proportionality of such regulation has to be assessed (Nyhan, 2020).

Concerning regulations in general, it also needs to be taken into account that regulation which is only indirectly connected to the respective public health intervention might exert spillovers on people's participation and compliance. This is pointed out by Lucas et al. (2020), who argue that stricter legal enforcement of self-isolation measures for people infected with SARS-CoV-2 could be associated with a decreasing willingness to report an infection and to comply with contact tracing

measures. This could be explained by stricter regulations increasing the individual costs of compliance.

5.6. Technology design

To ensure high participation, DPHIs need to address the digital divide. In most countries, parts of the population does only have limited or no digital skills or lack the financial resources or willingness to adopt more advanced digital technologies. DPHIs should therefore have low requirements regarding the technology they are delivered through and the digital literacy needed to use them. Reducing such barriers to participation ensures equitable access to the intervention and contributes to achieving the highest possible adoption rate (Loi, 2020).

Furthermore, the perceived costs of participation should be minimized by technological means as much as possible. A DPHI needs to be of low complexity, convenient to use and the necessary tasks for participating in the intervention should be obvious, short and easy (Trang et al., 2020). To increase convenience, it can also be helpful to integrate several DPHIs into one technology solution - for instance, a universal public health app with different functions like providing health-related information, communicating public health alerts and enabling digital contact tracing (Li et al., 2020). Since the perceived costs of using a technology might only weakly correspond to the objective costs, experimental tests with potential users should be performed in advance whenever possible, such that technology designers can take this feedback into account. In this regard, it should also be tested how different demographic groups perceive the costs of technology usage (Read, 2019). If a DPHI is targeted at a certain group within society, for instance, at people of older age or mothers of infants, the design of the intervention should be adjusted according to the skills and user behavior of the respective group.

Concerning the technology design it is also worth considering who develops and runs a DPHI. Survey evidence suggests that the trust in and the reputation of the institution or company that designs and implements an intervention plays an important role for the participation decision. Keusch et al. (2019) find in a survey among 1,947 people that the willingness to download an app in order to participate in data collection for research purposes is higher when the study is conducted by a university than when it is conducted by a research company. Simko et al. (2020) document that people are more willing to adopt a contact tracing app that is developed by a company or institution that they already know and trust with regard to privacy and security issues. In their survey, this results in higher support for Google and Apple as potential app providers, compared to Facebook and ByteDance. They also document higher trust in universities as DPHI developers, compared to government institutions and activist groups.

Furthermore, participants' trust in the technology could be increased by giving adopters control over the data they share through the DPHI (Keusch et al., 2019). Asking people for consent each time their collected data is accessed or used for further analysis might be a means to implement such data sovereignty. The net effects are not necessarily positive, however. On the one hand, such features increase

transparency and user autonomy and might mitigate concerns about surveillance and privacy invasion, which might lead to a positive effect on participation (Mello & Wang, 2020). On the other hand, the need for explicit consent draws attention to privacy concerns (Marreiros et al., 2017) and increases effort.

Finally, the technology of DPHI should be reliable. DPHI participation might be adversely affected by the diffusion of incorrect information via the system or technical problems. The accuracy and reliable functioning of an intervention therefore needs to be ensured before starting the roll-out process in order to avoid undermined trust as a consequence of errors (Bonardi et al., 2020; Kaptchuk et al., 2020). Errors occurring during the deployment of a DPHI need to be communicated clearly and transparently.

6. Digital contact tracing as a digital public health intervention

6.1. Benefits of digital contact tracing

The key non-pharmaceutical intervention to manage epidemics is to isolate the infected as well as tracing, testing and – if necessary – isolating their contacts. The SARS-CoV-2 pandemic has shown, that such test-trace-isolate strategies are limited by the capacity of public health authorities to reconstruct chains of infection. Furthermore, tracing contacts has natural limits in the memory of infected people of who they met and in the anonymity of casual contacts in public spaces. These problems might be exacerbated by characteristics of the pathogens and the illnesses they cause. In case of SARS-CoV-2 and COVID-19, the illness caused by the virus, a significant share of the transmissions appear to take place before the transmitting person has developed symptoms and the median time period between the infection of a person and the onward transmission to another person is only about 5 days (Cheng et al., 2020; Ferretti et al., 2020). These characteristics increase the length of the potential chains of infection and can lead to a “curse of dimensionality” for contact tracing. When contact tracing either becomes infeasible or too inaccurate, stricter measures to contain an epidemic might become necessary. During the SARS-CoV-2 pandemic, this included the closure of businesses, schools and cultural life as well as limits to the freedom of movement. Such measures bear significant economic and social costs. Mulligan (2020), for instance, estimates that each workday at which non-essential businesses and activities are shut down in the US due to lockdown measures reduces the country’s economic welfare by about 28.2 billion US-Dollars.

A technological way to increase the capacity, speed and scope of contact tracing is digital contact tracing. The basic idea is that a mobile application records data on meetings or encounters of users of the application. If an app user tests positive for a pathogen after such an event, the data collected by the app can be used to reconstruct at-risk contacts and thereby parts of potential chains of infection. Ideally, the app includes the functionality to inform these contacts at high speed, to arrange clinical tests for the pathogen and to organize quarantine. In the case of the SARS-CoV-2

pandemic, Ferretti et al. (2020) estimate that widely adopted digital contact tracing technology could even deem mass quarantine (“lockdown”) unnecessary.

6.2. Approaches to digital contact tracing

Digital contact tracing technologies differ in a number of dimensions. One design dimension is whether it tries to record locations or proximity to other technology users. Location could be recorded through GPS sensors included in most modern smartphones or through location triangulation with the help of cell-phone masts. Proximity could be measured through the strength of Bluetooth signals or ultrasound signals, which most modern smartphones are capable of sending and receiving. All these technologies could also be used together, potentially balancing off each other’s weaknesses. Given the prevalence of the necessary sensors, smartphones are a natural candidate for implementing contact tracing technology in the form of a mobile app. During the SARS-CoV-2 pandemic, Bluetooth-based proximity tracing became the norm.

Another design dimension is how the records of locations or encounters are stored and how they are used to inform technology users about their status. The two most frequently discussed models are a “centralized” and a “decentralized” approach. Contrary to what the terms might suggest, there exists a central server run by a central party in both models. The app of a user records the location or proximity relative other app users. The app users identify each other with an identifier, such as a hash key. If priority were to be given to data protection, this hash key could be randomly generated and regularly changing. In case of an infection, data is transferred to the central server. Under the decentralized approach, this data only contains the hash key of the infected app user. Other app users have access to the centralized server, can compare their collected list of keys with the keys of infected app users stored on the server. If their list of keys includes the key of an infected app user, the app can inform its user about the at-risk contact. Under the centralized approach, the data transferred to the server upon an infection contains the hash keys of the user as well as all recorded at-risk contacts. The central authority then can transparently redraw potential paths of infections and inform at-risk app users. In both cases it is necessary to develop a logic according to which at-risk contacts are defined, such as how long a user needs to have exposure to other users and at what distance.

Other design dimensions include how an infected app user is identified in the first place, how this information is fed into the app, whether such reporting to the app is mandatory or voluntary, how users can or have to react to at-risk contacts, whether and how public health authority contact is established and how follow-up testing procedures are integrated into such an app.

During the SARS-CoV-2 pandemic, several countries introduced digital contact tracing. China, South Korea and Israel were particularly fast to use mobile phone location data for contact tracing and quarantine surveillance (Amit et al., 2020; Budd et al., 2020). The “TraceTogether” app introduced in Singapore in March 2020 was an early centralized approach to app-based digital contact tracing via Bluetooth

(Mello & Wang, 2020). In the following months, a number of public and private initiatives in several countries started to develop solutions for digital contact tracing. To mitigate privacy concerns, many approaches, such as “PACT” and “DP-3T”, are built on privacy preserving protocols. These protocols use a Bluetooth-based decentralized design, with Apple and Google providing specialized interfaces in their respective smartphone operating systems in order to give more elaborate access to Bluetooth sensors. Germany, Switzerland, Italy, Canada, Japan, Malaysia and several other countries built their contact tracing apps base on these interfaces. The majority of these apps uses randomly generated, frequently changing hash keys to anonymously identify their users and require user consent for reporting the personal identifiers to a central server after being tested positive for the virus (Sharon, 2020). Starting October 2020, several national apps are planned to become interoperable, particularly in order to improve their utility in border regions and with increasing international travel (Salathé et al., 2020).

Digital contact tracing requires several user activities to work effectively and each activity involves private costs and benefits as well as public benefits. As pointed out by Bonardi et al. (2020), contact tracing apps such as the ones introduced in Germany and Switzerland which are based on fully voluntary participation require users to take several steps to function effectively. Users need to download the mobile application, keep it constantly active on the smartphone they carry with them, react to the alerts received via the app (e.g. self-isolation, getting tested) and they need to be willing to report their own SARS-CoV-2 infection to the app. These activities involve private costs, such as effort, perceived risks to privacy, disutility from receiving unpleasant information (e.g. about being at risk for having contracted the disease), and public benefits, such as the possibility to control virus spread at the community level. Costs and benefits weigh differently in different activities. Keeping the app active on one’s phone and receiving alerts arguably also involves significant private benefits as a user might be able to learn early on about her own infection and thereby protect those she cares about and adjust her own behavior to reduce the risk of a severe course of the disease. However, private benefits are arguably not apparent when revealing one’s own infection to the system. In this case, private costs have to be weighed against purely public benefits which might result in cooperation problems. Another relevant aspect is that strong network effects are present in the case of digital contact tracing. The benefits from digital contact tracing grow exponentially in the number of participants (Ferretti et al., 2020).

6.3. Participation in digital contact tracing

Surveys conducted during the first wave of the SARS-CoV-2 pandemic suggest a relatively high willingness to participate in digital contact tracing across several countries. Altmann et al. (2020) conducted online surveys among almost 6,000 participants at the end of March of 2020 to assess the potential for digital contact tracing in Germany, France, Italy, the UK and the US. Across all five countries, the majority of survey participants expressed their willingness to install a digital contact tracing app. Support was found to be above 65 percent in all countries, ranging to

up to 85 percent in Italy. More than 90 percent of survey participants in all countries claimed that they would at least probably comply with an app alert, meaning that they would self-isolate when notified. Concerns about government surveillance, general privacy risks and psychological stress are named as the main reasons against participation in the intervention. The protection of family and friends, a general responsibility towards the community and receiving information about one's own infection risk were the main motives favoring the installation of the app. These results are mostly confirmed by Ebert & Widmer (2020) who find that 68 percent of survey participants in Switzerland respond that they would probably install a privacy preserving contact tracing app. Kaptchuck et al. (2020) and Simko et al. (2020) find in surveys conducted in the US intended participation ranging from 70 to 80 percent for apps with a high level of privacy protection. The survey by Kaptchuck et al. (2020) also points to the importance of the accuracy of digital contact tracing for the willingness to adopt it. In contrast to those findings, Blom et al. (2020) document a willingness to adopt the – at the time – recently launched German contact tracing app of only about 35 percent among the 3,276 participants in their survey. They point to the fact that this is driven by older people showing a high willingness to adopt but lacking technology access and digital literacy, while younger people have access and ability but a lower willingness to install the app.

Empirical evidence shows adoption rates of digital contact tracing that are significantly below the about 60 percent required in a population to suppress the spread of the pandemic without any further public health interventions (Ferretti et al., 2020; Hinch et al., 2020). Figure 2 plots the total number of downloads of the German, Singaporean and Swiss contact tracing apps since their respective launch dates. Adoption grows strongly at first but growth decelerates relatively quickly. It is important to note that not everybody who downloaded the app does actively use it. Salathé et al. (2020) report that between July 23, 2020 and August 31, 2020 1,054 SARS-CoV-2 cases, 12.4 percent of all confirmed cases in Switzerland in this period, have been reported by users to the contact tracing app.

7. Recommendations for fostering participation in digital contact tracing

The relatively low adoption rates of digital contact tracing apps during the SARS-CoV-2 pandemic illustrate, that wide participation in DPHIs can be difficult to come by. Since the technology and implementation processes are still evolving at the time of this writing and strategies for digital contact tracing vary widely around the globe, it is difficult to get a detailed picture of which measures were taken so far to increase participation. In this section, we build on the framework developed in chapter 5 and develop general recommendations on how participation in digital contact tracing could be fostered. We assume that participation is voluntary and that participants have to be convinced of adopting and using a contact tracing app.

7.1. Information provision

Involving prominent and trusted figures from different ideological and political groups in information campaigns and letting them deliver a consistent message can increase the effectiveness and reach of such campaigns. This is a measure to counter false information about the risks and benefits of digital contact tracing with consistent information provided by credible sources. The goal is that potential participants update their beliefs according to this information, which might lead to increased perceived benefits and reduced perceived costs of participation and thereby to increased willingness to adopt the app. Well-known science journalists, scientists and physicians could be particularly effective communicators, since trust in them might be reinforced by their expertise. The messages delivered should be based on best scientific evidence, transparent and clear. As the understanding of the public health threat evolves, recommendations might need to change. In such cases, transparency can help to avoid misunderstandings and the formation of miscalibrated expectations. The same applies to potential technical problems with a contact tracing app. Furthermore, it is also important to avoid a false sense of safety associated with participating in digital contact tracing which could lead to risky behavior. It should be clarified that digital contact tracing is a complement but not a substitute for other measures, such as physical distancing and wearing of a face mask (Raskar et al., 2020).

Messages about digital contact tracing can be framed to influence people's perceptions about the costs and benefits of the intervention. A focus on the public benefits of participation, on participation as a way to contribute to a public good, can appeal to people's intrinsic motivation. However, such an approach alone is not necessarily effective when people perceive significant private costs. Therefore, the private benefits from participation and the benefits to one's immediate social environment should be pointed out to further enforce incentives for participation (Bonardi et al., 2020). A clear presentation of the trade-offs involved might also foster adoption. For instance, clearly stating that the alternatives to digital contact tracing are an aggravating public health crisis with increasing death toll or major lockdown measures with heavy economic consequences could increase support for this relatively mild intervention. Correcting misperceptions about the pandemic like a lack of comprehension of its exponential growth dynamics might further increase the efficiency of such messages (Lammers et al., 2020). Digital contact tracing could also be compared to traditional contact tracing or to well-known other apps, which people find acceptable despite their associated privacy risks (Bonardi et al., 2020; Buzzell, 2020). This might decrease the relative perceived costs of digital contact tracing by putting them into context.

Furthermore, false information on privacy risks, increased government surveillance or other potential concerns need to be counteracted. One instrument could be to clearly mark verified information, for instance, on government or public health authority's websites or social media accounts. Involving experts and institutions that are perceived as independent in the communication of verified messages could increase their credibility. Another instrument could be the flagging

of false information on social media platforms and other media used to spread nonfactual claims (Nyhan, 2020; Swire-Thompson & Lazer, 2020).

The effectiveness of information campaigns could also be increased by targeting. Tailored messages could be delivered to people with the highest risk of spreading the virus, for instance young and mobile individuals who interact in large social networks. Even if a similar message is communicated to all parts of society, the intensity of communication effort should be varied according to where a stronger adoption would have greatest impact. One obvious way is to address regional variation in the contraction of the pathogen, with higher exposure areas being targeted with information campaigns to a greater extent. This is also in accordance with the local public good character of digital contact tracing. An individual's or community's benefits from digital contact tracing depend mostly on the adoption rates among the people within that community, since community members are most likely to encounter each other regularly (Vaithianathan et al., 2020). The benefits of the intervention – especially to an individual's close social environment – could quickly become salient and positive experiences within one community can lead to spill-overs in adoption behavior to other communities through social learning. If reliable knowledge of social networks within society exist, it might also be feasible to use information on the location of an individual within the social graph for micro-targeting, where information is provided to specific individuals with the intention of them effectively spreading in the social network. However, the necessary information on actual social networks is usually difficult to come by.

7.2. Explicit incentives

Material rewards can incentivize the participation in digital contact tracing if they are complementary to intrinsic motivation. To achieve this, referral bonuses or other forms of explicit incentives for app adoption should be accompanied by a clear message about their substantiation. The moral and prosocial component of participation should be explained, community feedback needs to be permanently collected and the observable effects continuously evaluated (Kranton, 2019). Survey evidence from the US by Frimpong & Helleringer (2020) indicates, that receiving a payment in exchange for downloading a contact tracing app significantly increases user's willingness for adoption. Stated and revealed preferences might differ, however. One way of circumventing crowding-out effects might be to allow for voluntary sorting into either incentivized or completely intrinsically motivated app adoption (Meyer & Tripodi, 2018). Although the long-term effects of such schemes might be unclear, the more immediate observed benefits might balance out longer-term costs of adoption.

Not only direct payments for adoption, but also other material incentives could be used to foster participation in digital contact tracing. Depending on the public health system, free pathogen testing for those who received a notification by the app and direct or financial support for those who voluntarily self-isolate when receiving a notification could decrease the perceived costs of app usage and thereby increase adoption (Bonardi et al., 2020). Furthermore, the provision of smartphones with a

pre-installed contact tracing app for free or at discounted prices to those who do not own a smartphone could help to ensure wide access (Loi, 2020). While such schemes might appear costly at first sight, the benefits could very well outweigh the immense costs of other public health interventions.

Besides material incentives, non-material incentives for adoption should also be considered. Awards and social recognition could increase the perceived benefits of participating in digital contact tracing. Traditional awards – similar to those often presented in the context of blood donations – could be presented to people who continuously participated in digital contact tracing for a certain period of time or referred a certain number of contacts to the app. However, the scalability of such awards is limited since awards need to be kept short in supply to preserve their value as a sign of social distinction (Frey, 2007). They might therefore not be suitable to incentivize participation and adoption by many millions of people. Other forms of social recognition might be more efficient. First, the exclusive provision of items to app users that make their participation visible to others could serve this purpose – for instance, a t-shirt or a mug stating ‘I contribute to stopping the pandemic’. Second, sending a personalized text message to thank an app user for the continuous use of the app or providing users with a purely symbolic ‘gold status’ in the app as a form of referral bonus or reward for continued use. Even though such signs of recognition are not visible to others, they still might enhance self-identification with the community and increase intrinsic motivation (Gallus, 2017). However, it has to be noted that trust in and respect towards the institutions – which are in most cases related to the government – presenting such forms of social recognition is needed for these measures to be valuable to individuals (Frey, 2007). When trust in public institutions is low, this form of explicit incentives might therefore fail to have a significant positive effect or might even lead to public ridicule and rejection.

7.3. Nudges

Nudges offer a variety of possibilities to foster the participation in digital contact tracing. Making the installation of digital contact tracing the default option could be particularly effective. A contact tracing app could be automatically installed on all smartphones with the regular updating process but users remain free to stop the installation at any time or de-install again afterwards (Bonardi et al., 2020). Altmann et al. (2020) find in their study that more than 60 percent of survey participants express to agree with an opt-out design for digital contact tracing. However, such a nudge might also undermine people’s sense of autonomy and their trust in the providers of the DPHI. A less invasive option could be to send text messages reminding people of the public and private benefits for adoption and providing a link for installing the app.

Another option are social nudges that signal to people that others also participate. Authorities might, for example, frequently publish and visibly communicate data on the share of the population that adopted the contact tracing app in a certain neighborhood. Or the app might inform individuals how many other people who use the app they encountered in the past week to encourage sustained

usage. Of course, such approaches only work when the adoption rate is sufficiently high. They are not a tool to boost adoption in early stages. Instead, they might even reinforce trends of low adoption so that this policy tool should be used with care (Bonardi et al., 2020; Michalek & Schwarze, 2020). People might also update their beliefs on the benefits of app usage when the negative consequences of not using the app are made more salient. If sufficient information on the effects of the app are collected, it might well be feasible to provide estimates for the counterfactual outcomes had digital contacts tracing apps not been adopted and to present them in an easily comprehensible format (Bonardi et al., 2020).

7.4. Regulation

A transparent and reliable regulatory framework for digital contact tracing can build trust and mitigate privacy concerns. The time period in which digital contact tracing is used should be limited. The operator of the digital contact tracing system should be a trusted and potentially civilian institutions to mitigate concerns over government surveillance. The data collected by the app should be minimized to what is needed for efficient contact tracing and access to that data should be restricted as much as possible. Mandating a privacy preserving approach to digital contact tracing by law could be helpful to foster participation. Furthermore, a guarantee that participation remains voluntary or conditionally voluntary encoded in law could be perceived as more reliable than lip service by politicians and public health authorities. The same applies to the establishment of an oversight board to ensure the compliance with the regulatory framework (Amit et al., 2020). Governments fostering the adoption of digital contact tracing also need to consider the potential adverse effects that other public health regulations, such as quarantine measures, can have on the willingness to adopt and use digital contact tracing (Lucas et al., 2020).

7.5. Technology design

Digital contact tracing apps should be designed such that the costs of participation are as small as possible while the benefits are salient and easily comprehensible. One aspect of this is the compatibility among different contact tracing systems – possibly also across national borders – to maximize network effects and thereby also the individual and public benefits of the intervention. Using the same technological design across countries or public health authorities is a prerequisite to interoperability. Furthermore, digital contact tracing apps should have low technological requirements, such as limited memory and battery usage on smartphones, and should be easily downloadable and usable even for those with limited digital skills. Trang et al. (2020) conduct a survey study in which they present different hypothetical scenarios for a contact tracing app to their respondents. They report that a highly convenient app design where the app operates smoothly in the background with automatic updates and requiring low levels of battery power can significantly increase the willingness to use the app compared to a lower convenience

design. This is especially true for undecided participants who do not yet have an established opinion on digital contact tracing.

An important technological design feature is privacy preservation. Several surveys (Trang et al., 2020; Kaptchuk et al., 2020) suggest the importance of a privacy-preserving app design to decrease the perceived costs of adoption. High trust in the developers and operators of the app based on past experiences might also mitigate privacy concerns. Simko et al. (2020) report relatively high levels of trust in Google and Apple and in their products like Google Maps and Apple Maps. An integration of digital contact tracing in an app like Google Maps could therefore mitigate concerns, and also increase convenience (since potential users already have the app installed and know how to operate it) and facilitate opt-out approaches (contact tracing could simply be added to Google Maps with a regular update with the option to de-install the add-on). However, such an approach also involves significant concerns when a public health intervention is tied closely to a commercial product.

Besides privacy preservation, the accuracy of contact tracing should be sufficiently high. Kaptchuk et al. (2020) find that the accuracy of a contact tracing app plays a significant role in the participation decision. According to their findings, false negatives – i.e. an at-risk user is not notified by the app – affect user perceptions more than false positives – i.e. people are notified to be at risk even though they had no risky encounter. A low app accuracy might lead to reduced perceived benefits from its usage and increase people’s uncertainty. Of course, false negatives are unavoidable, especially as long as the adoption rate of digital contact tracing remains low. Communication about this fact has to be transparent. Bonardi et al. (2020) suggest that the parameters that determine when a notification is sent and when not should be set carefully to ensure a reasonable level of sensitivity but at the same time avoid a too high rate of false positives that might discourage users from app usage. An early test phase with selected users – like those who are especially technology affine or have a better understanding for how the app works – could help to evaluate and adjust the system to prevent larger systematic errors once the app is rolled out in the whole population.

To increase the immediate benefits that people receive from installing and using a contact tracing app, developers might also consider to add additional features to the app. These could be, for instance, the provision of general recommendations regarding the behavior during the pandemic or frequently updated information on the regional development of the pandemic and on local hotspots that should be avoided. App usage would involve private benefits even before a user receives an alert and it becomes more salient that the app is actually working (Bonardi et al., 2020). Li et al. (2020) report that in their survey the hypothetical provision of information on local hotspots of SARS-CoV-2 infections adds to user’s perceived benefits from app usage and may increase adoption rates.

Privacy preservation can be in conflict with such other activities to foster participation. For instance, providing detailed information on the positive effects of digital contact tracing in the community of an app user requires data collection based on location, which might be perceived as privacy-invasive. More generally, the

ongoing evaluation of digital contact tracing as a means to break chains of infections requires a certain level of data collection, which might raise privacy concerns. One way to counter these concerns could be to provide a second version of a given contact tracing app, which collects additional data. This app could be advertised to a random sample of citizens, with acceptance being monitored and making potential selection effects in participation visible. This sample could then be used to evaluate the efficacy of an app.

8. Recommendations for further research

All these proposed measures to foster participation would need to be properly evaluated. Ideally, the introduction of digital contact tracing apps is designed such that all data necessary to evaluate the efficacy of the respective design is collected. However, intentionally introducing experimental variation when rolling out an app requires levels of willingness to learn, scientific sophistication and technical literacy rarely observed in political circles and in public health authorities. During a public health crisis, these requirements might be fulfilled even less. In the absence of such experimental variation, quasi-experimental and other observational analyses could sometimes provide an approach for evaluation. Surveys and experiments with potential and actual app users could also provide a means to evaluate certain aspects of the related cost-benefit calculations, potentially even in real-time. However, given the multi-dimensionality of the measures to foster participation and their interdependence, only cooperation with public health authorities and other parties involved in operating digital contact tracing systems and intentional testing will lead to reliable evaluations. It is also an open question, to what extent successful dissemination strategies differ between DPHIs.

More generally, the problem of increasing participation in DPHIs has similarities with problems occurring in development economics. Similar to development economics, hardly any particular measure to foster participation is likely to generate all necessary improvements on its own. It is more likely, that a carefully selected set of different measures induces greater adoption and usage. Implementation details, such as the format of information provided by an app, could matter greatly. The research approach described by Duflo (2017) as “the economist as a plumber” will be more suitable than that of an “economic architect”. The process of properly evaluating the different measures to foster participation in DPHIs is potentially long and tedious rather than a one-off effort with clear results. But similar to development economics, the scale of the problem which digital public health interventions have the potential to address should provide sufficient encouragement to pursue this line of research.

One obvious general public health problem, which can be addressed by DPHIs, are epidemics other than SARS-CoV-2. Digital contact tracing could be particularly helpful in such situations. Since most developing countries have leapfrogged to smartphone devices, the additional technological requirements would be modest even for them. Digital interventions to increase public health could also be a useful tool to move from national public health initiatives to global public health

initiatives. Viruses such as Ebola do not stop at country borders. If digital public health interventions were to be made freely available, interoperable and easy to adopt, they could provide the technological base for greater international cooperation among health authorities to tackle such pandemics.

But digital public health interventions can reach much beyond managing immediate crises, as illustrated previously. They can also play a role in tackling slower-moving but nonetheless widespread health issues, such as cardiovascular diseases, the number one cause of death globally. For instance, experiments by Perez et al. (2019) with Apple's smartwatch suggest, that optical sensors on wearable devices can potentially predict atrial fibrillation. Another experiment by Chandrasekhar et al. (2018) assesses the potential to measure blood pressure via a sensor integrated in a smartphone as a further means to monitor cardiovascular conditions. However, to make such approaches broadly available, large-scale data sets are needed, which rely on voluntary data contributions. Such voluntary data donations are also a prerequisite to develop personalized and precision medicine. Digital technologies enable the large-scale collection and analysis of individuals' genotypic and phenotypic data if people are willing to share this information. Based on such analysis patients could receive tailor-made treatments for diseases, such as cancer, that take into account individual characteristics, which can result in increased efficacy, efficiency and safety of the respective therapy (Kohane & Altman, 2005; Kohane, 2015).

However, widespread adoption and usage will be critical to the success of most such digital public health interventions. More contributions to the state of knowledge on how to accomplish this are needed.

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