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Mobilizing Citizen Data for Society 5.0

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Chapter 1

Introduction

"The future we want must be created.
Or else we'll get one we don't want."[5]

–Joseph Beuys

1 Introduction

Technological progress has always shaped the lifestyles, cultures and communities of mankind. The extent and ambivalence of this shaping increased dramatically with the first wave of industrialization that rolled from Europe across large parts of the world in the late 18th century. Early industrialization created an urbanization boom, fueled wage labor and changed the pillars of economic growth. It also clearly illustrates an essential characteristic of technological progress that is still evident today: the ambivalent nature of its effects on the well-being of society. While some parts of society benefit from technological progress, it creates injustice, inequality and structural disadvantages for others. This ambivalence has marked the history of technological progress over the past 250 years up to the present.

Scholars have long been concerned with the question of how the well-being of society and its individuals change in the face of technological progress, and how its ambiguity may be resolved (e.g., Ashton 1948, Crafts 1985, Deane and Cole 1962, Rostow 1960). The pressure and responsibility to find answers have never been greater than today. After all, never before in history has progress accelerated at the current pace: not only is technology developing exponentially, but the extent to which technologies are shaping people's working and private lives is increasing as well (e.g., Adedoyin et al. 2020). Despite the complexity and diversity of today's innovations, a majority build on one key resource: data. Data are the "new oil" of our century as they facilitate new business models and economic sectors, the training and operation of technologies as well as the optimization of existing systems and processes (e.g., Kusiak 2009, Sorescu

[5] Translation by the author. Original quote: "Die Zukunft, die wir wollen, muss erfunden werden. Sonst bekommen wir eine, die wir nicht wollen." Joseph Beuys (n.d.).

2017). As today's driver of technological progress, data have a correspondingly central role in leveraging this progress for social welfare (UN 2014).

Data emerge through various sources. Individuals in particular produce large amounts of data in their everyday lives. By using, for example, smartphones, apps, digital assistants, and social media platforms, individuals automatically provide their data to the providers of such products and services (e.g., Acquisti et al. 2013, Xu et al. 2009). The analysis of the thereby provided data not only reveals detailed information about behavioral patterns, but also about various other attributes such as personal values and beliefs, likelihood of diseases, creditworthiness, social behavior, and moods (e.g., De Choudhury et al. 2013, Tan et al. 2016). These valuable data sets arise in particular from the use of products and services that are offered by the private industry. The private industry has an incentive to operate those products and services because it can use thereby collected data to generate additional profits, e.g., through personalized offers or the sale of data to third parties (e.g., Esteve 2017). Social welfare-oriented actors, such as governments or non-profit organizations like the United Nations (UN), instead use data to generate social benefits. However, due to limited resources, welfare-oriented actors are rarely providers of products and services that the public uses in a way in which they would provide sufficient quantity and quality of personal data. Hence, especially those organizations hold large amounts of data that tend to utilize them for profit rather than for the benefit of society (World Bank 2021). As a result, the vast potential of data to guide technological progress and to enhance social welfare remains underutilized.

The question of how technical progress can benefit society inevitably implies the question of data governance. Among politicians and academics, a specific term is currently emerging for a vision of society in which data and data-driven technology is primarily mobilized for the goal of maximizing social welfare and individual well-being: Society 5.0 (e.g., Cabinet Office 2016, Deguchi et al. 2020, Salgues 2018). In this concept of society, the ambiguous effects of technological progress would finally be resolved. Following the vision of Society 5.0, this dissertation aims to make a small contribution to increasing the availability and quality of data for the benefit of social welfare. For this purpose, it focuses on a promising approach that is currently receiving increasing attention in academia and practice alike: the active participation of citizens.

First, citizens may deliberately create new data sets that did not exist before, e.g., through measurements, documentation, or surveys (e.g., Lämmerhirt et al. 2018). Second, citizens may share data sets with social welfare-oriented actors that they already automatically generated through the use of private industry products and services (World Bank 2021). Both approaches contribute to reallocate data and increase their quality in favor of society and its individuals.

This dissertation takes an interdisciplinary approach to provide a nuanced perspective on civic participation in enhancing data availability and quality. Paper I and Paper II of this dissertation use online experiments and surveys to generate insights into the structural, situational and psychological factors that drive individuals' willingness to share personal data for social welfare. Both papers are rooted in the literature on cooperative behavior with uncertain payoffs and decision-making under risk. Paper III takes a practical approach and involves the technical development and initial testing of a technology that enables citizens to generate new data sets for social welfare. Table 1 gives an overview of the dissertation papers.

Table 1. Overview of Dissertation Papers

Paper	Title	Author(s)
I	The Social Dilemma of Big Data: Donating Personal Data to Promote Social Welfare	Kirsten Hillebrand Lars Hornuf
II	The Role of Fear and Trust when Disclosing Personal Data to Promote Public Health in a Pandemic Crisis	Kirsten Hillebrand
III	“KlimaKarl”—A Chatbot to Promote Employees‘ Climate-Friendly Behavior in an Office Setting	Kirsten Hillebrand Florian Johannsen

Due to the particular dynamics and scope of the topic, the existing literature on civic participation—both when donating existing data and when generating new data sets—is still incomplete. This dissertation strives for new puzzle pieces to narrowing this research gap by specifically considering up-to-date contexts and technologies. The remainder of this dissertation proceeds as follows: chapter 2 outlines the impact of technological progress on social welfare among past industrial revolutions, and introduces the concept of Society 5.0. Chapter 3 highlights ethical challenges of a data-driven society and proposes civic participation in data governance as a potential solution. Chapter 4 presents the key section and empirical results of this dissertation. Chapter 5 presents a discussion of the findings and chapter 6 concludes.

Chapter 2

Society in the Course of Technological Progress

2 Society in the Course of Technological Progress

2.1 The Industrial Revolution

The industrial revolution is a global process and, since its beginnings at the end of the 18th century, has significantly changed how people live, how societies function and how economies achieve progress. It continues to shape our modern world. A review of the socio-economic effects of technological progress in the past is central to the understanding and specification of how progress ought to be guided differently today. The story of industrialization over the last 250 years is usually told through four sequential industrial revolutions (e.g., Bahrin et al. 2016, Hudson 2014, Stearns 2020).

An industrial revolution is a disruptive and long-lasting change in industry that is not limited to one technology and affects all social classes, labor markets and sectors of the economy (Grübler 1998). The first industrial revolution originated in Great Britain. Manufacturing with increased energy through water and steam enabled the operation of machines and facilitated the production of chemical substances and metals such as iron (Ashton 1948). The British textile industry in particular benefited from these developments. From Britain, the first revolution spread across Europe to the United States (Allen 2009). A new modern era dawned in Europe and North America, enabling economic boom through faster mining, steam-powered rail transport and cargo shipping, steel production and more (Mohajan 2019a). The socio-economic changes were both massive and ambivalent. Whether citizens profited or suffered from this wave of technological progress significantly depended on the social class they belonged to.

Progress led to several desirable developments for society. The industrial revolution in Britain was closely linked to an agrarian revolution, in part because the agricultural sector supplied the industrial sector with labor and resources (Allen 1994). Prior to the first wave of industrialization, about 80 percent of the British lived in rural areas and in severe conditions due to lack of sanitation and health care, water pollution, and poverty (Mohajan 2019a). With the industrial revolution, rural areas turned into urban agglomerations, where craftsmen and farmers were hired in factories (Clark 2007). A rapid urbanization emerged (Sachs 2005). Energy was cheap, production increased and the employment of unskilled labor as well as the general labor wage level rose (Allen

1992). With the economic development, better general sanitary conditions and the production of medical devices, populations grew, too (Murmann 2003). In Britain, for example, the infant mortality rate dropped, and the overall birth rate climbed significantly. Also, infrastructure improved worldwide (Sachs 2005). Many new and improved street kilometers, an expanded railroad network and waterways accelerated the transportation of goods and people (e.g., Beker and Lipsey 2002, Chandler 1981, Clark 2007). Simultaneously, mass production allowed for better housing, diets, and clothing (Mohajan 2019a).

However, industrial progress was not beneficial for all citizens, especially not for those belonging to low social classes. While wage levels rose in general and a new middle class of bankers and factory owners was establishing, the wages of factory workers in particular were extremely low (Rostow 1960). Workers did not financially profit from economic growth and suffered from diseases and poverty (Crafts 1985). Accordingly, workers reacted with revolts and strikes, which led to civic formations such as the first trade unions (Hobsbawm 1968, Rule 1998). The factories also employed children and women, but at considerably lower wages than male workers (Burnette 1997). In some British factories, children even made up about two-thirds of the workforce, working in disastrous conditions and receiving no schooling (Galbi 1994). Between 1800 and 1850, the number of European cities jumped from 22 to 47. This rapid and unstructured urbanization implied chaos and crime and led to many families living in poverty without light or sanitation (Flinn 1966). The environment also suffered significantly from water and air pollution, e.g., from factory emissions and toxic waste discharged into rivers.

Despite social benefits, the first industrial revolution increased inequality on several levels. First, within countries and societies: The living conditions of low-income groups hardly improved by 1850, while the living conditions of high-income groups improved significantly due to better education and cheaper goods (Deane and Cole 1962, Rostow 1960, Wrigley and Schofield 1981). Second, the wealth gap also widened globally: industrialized countries not only sourced their raw materials from underdeveloped countries and traded slaves, but also exported the manufactured goods back to non-industrialized countries, creating and dominating new markets (Mohajan 2019a).

The second industrial revolution began around the end of the 19th, beginning of the 20th century and extended the advances of the first revolution, especially in Europe and North America. While machines and techniques were completely re-imagined in the first revolution, the second industrial revolution is characterized by understanding and optimizing those inventions scientifically. Existing technologies advanced to become more efficient and expanded from insular areas to diverse products and activities (Mokyr 1998). This parallel, multifaceted and constant further development of innovation is understood as "microinventivity" (Mokyr 1998). Pre-existing resources such as gas and water supplies in cities, safe and fast railroads, or the production of affordable steel only became mainstream after 1870 (Atkeson and Kehoe 2001). The first factories grew significantly to reduce costs per output through economies of scale, and production processes gained efficiency by dividing up work tasks (Sabel and Sabel 1982). Henry Ford's automobile manufacturing company became known for this production and labor design and, along with Frederick Taylor, still stands for productivity increase through the division of labor today (Maier 1970, Rinehart 2001). A number of new discoveries are characteristic of this period, such as electricity, the electricity-enabled expansion of communications technology, and the targeted use of chemicals (Mokyr and Strotz 1998).

From a social perspective, a massive migration flow marked the period of the second industrial revolution (Mohajan 2019b). While millions of African slaves were forcibly relocated by the end of the 19th century, more than seven times as many mostly uneducated Irish, Italians, Jews, Chinese, Russians, and other nationalities left their countries to participate in the economic boom in North America (Alexander 2009). Working conditions for uneducated workers, however, remained harsh, unhealthy and underpaid (Fink 1988). The gender and wealth gap did not narrow either (Gordon 2012). While strikes for better working conditions had been tolerated in England since 1870, they were still violently suppressed in the US at the beginning of the 19th century (Foner 1978). Even schooling for the lower income groups hardly improved. In the US, a functioning school system was especially challenged by over 200 different languages spoken by immigrated people (McCarty 2002). For the environment, widespread industrialization led to significant damage through habitat destruction, the use of chemicals in agribusiness, air and water pollution, and increasing CO_2 emissions (Mohajan 2013).

In the 1970s, the third industrial revolution introduced modern society. For the first time, technological progress considerably included the public and made everyday life easier in private households as well (Mokyr 1998). Mainstream technologies involved new forms of transportation such as airplanes and more affordable cars, as well as everyday luxuries such as elevators, typewriters, radios and telephones. Even though the mechanization of the agricultural industry was slow, food could now be preserved and facilitated a better diet of meat and vegetables (Mokyr 1998). The reinvention of medical devices such as scalpels and microscopes, as well as new research advances, allowed for better public health and medical care. During the third industrial revolution, infant mortality rates in Europe and North America dropped by around 50 percent (Mokyr 1998). Despite continued poor working conditions in the factories and difficult living conditions for the working class, more and more people benefited from higher wages, cheaper goods and a generally better standard of living brought by the technological and economic upswing of that time (Mokyr 1998, Richard 2010). The World Wide Web was evolving in its early stages and first became available to the public in 1991, towards the end of the third industrial revolution (Berners-Lee et al. 1992). The development of the World Wide Web marks a crucial shift from a purely industrial towards an information society (Naisbitt 1984, Stonier 1983).

From an industry perspective, the learning effects of the previous years had led to robot-assisted and automated manufacturing and production processes, causing factory productivity and output to soar significantly (Greenwood 1999). Concurrently, investment in information technology for production equipment increased dramatically. Massive cost reductions of goods and IT were the result. While the price of a computer in 1955 was 2 million US dollars, it was only 5,000 US dollars in 1987 (Yorukoglu 1998). A complementary initiator of higher productivity and cheaper prices was another form of energy generation in addition to fossil fuels. In the seventies and eighties, cheap nuclear energy fueled the rapid rise of telecommunications technology, electrical appliances and computers.

However, during the third industrial revolution, a productivity paradox emerged (Baily et al. 1988, Olson 1988). Despite the rising productivity of IT-based production, the productivity of labor temporarily stagnated. While the average gross domestic product generated per labor hour increased by 2 percent every year before 1970, the increase after 1974 remained at only 0.8 percent (Greenwood 1999). Countries like Germany, which had suffered high losses during the Second World War, were less affected by the productivity slowdown than, for example, North America and the UK (Romer 1987). The temporary stagnation of labor productivity was symptomatic of a fundamental change in the labor market during this period. While the first two industrial revolutions involved an increase in the demand for both skilled and unskilled labor, the third revolution led to an extreme increase in the demand for skilled labor (Liu and Grusky 2013). There is disagreement among researchers about the specific type of skills in demand. In addition to specific computer knowledge (Capelli and Carter 2000) required expertise might also have included creativity (Florida 2002) and general technological competence (Esping-Andersen 1993). Because the demand was greater than the supply, the pay for skilled workers increased significantly, leading to long-term income inequalities between different occupational groups (Acemoglu and Autor 2012, Autor et al. 2008). Since income inequality and the demand trend for educated workers with critical thinking skills and inductive reasoning have continued to this day, the third industrial revolution on the labor market is also referred to as the "analytic revolution" (Liu and Grusky 2013).

A greater public focus on environmental sustainability through an alternative energy supply further characterizes the third industrial revolution (Schlör et al. 2015). From the beginning of the 19th century, social and economic upswing was based on fossil fuels in particular (Burke and Pomeranz 2009). The environmental destruction and social danger associated with fossil fuels, e.g., air pollution and CO_2 emissions from coal-fired power plants and toxic waste from nuclear power plants, was now becoming apparent. Moreover, the limited availability of fossil fuels started to show, e.g., through exploding prices during the oil crisis (Jänicke and Jacob 2009). Societal and scarcity pressures encouraged intensive research and thus the first introductions of renewable energy through wind, solar and hydro power.

The widespread use of the Internet from the end of the 20th century and the transformation to information societies created the basis for the fourth industrial revolution in which we find ourselves today. In industrialized nations, the use of machines and technologies, software and hardware are now part of everyday life. Their added value and support are a commonplace. The volume of data is expanding so massively that we now measure it in zettabytes (10^{21}) (Emani et al. 2015), the amount of devices in the Internet of Things (IoT) is expected to increase from 27 billion in 2017 to 125 billion in 2030 (Kounoudes and Kapitsaki 2020), and information and communications technology (ICT) companies are among the most valuable in the world (UNCTAD 2018). The fourth industrial revolution is characterized by the extent to which big data is shaping technologies, business models, production processes and our daily lives.

The concept of Industrie 4.0 was originally introduced as part of the German High-Tech Strategy 2020 Action Plan, a national strategic initiative to promote smart factories by a joint working group representing academia, government and industry (Industrie 4.0 Working Group 2013). The working group's recommendations related to the use of the IoT and cyber-physical systems in order to cut production costs significantly. To this end, large amounts of data are collected for all physical, i.e., real-world manufacturing steps and levels. In a cyberspace, i.e., virtual place, the production steps are simulated, analyzed by artificial intelligence for optimizations and the results are fed back to the physical production system for direct consideration. Such smart factories allow for a greater flexibility in production, which can respond to shorter life cycles, global supply chains and higher product complexity. The capability of mass customization distinguishes the industry of the fourth from that of the third revolution (Deguchi et al. 2020). The basic concept of Industrie 4.0's smart factories has been adopted by various industrialized countries around the world, e.g., as a Connected Enterprise in the US (Morrar et al. 2017).

Even though Industrie 4.0 focuses on manufacturing processes, the fourth industrial revolution goes beyond. The overarching goal of IoT is to „enable things to be connected anytime, anyplace, with anything and anyone ideally using any path/network and any service“ (Vermesan et al. 2014, p. 8). This interconnectivity also includes various private areas and devices such as wearable gadgets or smart homes.

In addition to IoT, other innovative technologies such as blockchain, cloud storage, augmented reality, collaborative robots and chatbots promise a new era of progress that encompasses various sectors (e.g., Sherwani et al. 2020, Smutny et al. 2020, Wedel et al. 2020, Zhuang 2020). Yet all these technologies not only preserve the long-known tension between technological progress and social welfare, but arguably make the tension stronger than ever. After all, never before in the history of industrialization have data volumes, digital knowledge and technological progress advanced as rapidly as they are doing right now—exponentially (Adedoyin et al. 2020, Mashelkar 2018, Morrar et al. 2017). And never before have technologies intervened so extensively in the daily decisions and behavior of societies' members. The socio-economic changes are correspondingly massive. The fourth industrial revolution is changing business models in all industries and sectors, and thus the labor market as well. The changes include new demands on existing roles, the creation of new jobs and the elimination of existing ones.

The social trends that emerged in the third revolution are now intensifying, such as the division between skilled and unskilled workers (Morrar et al. 2017). With more flexible processes in production and data-based business models, the workforce needs to be assigned more flexibly, too. Employees need to be skilled at understanding more complex and holistic contexts. New technologies not only increase the demand for skilled workers, but at the same time replace in particular roles that were typically held by unskilled workers (Brynjolfsson and McAffee 2014). The countervailing effects of progress on skilled and unskilled labor, and the resulting increase in inequality, is reflected in various macroeconomic indicators. The share of labor compensation in gross domestic product is declining in various industrialized nations (Dosi and Virgillito 2019). Rising economic productivity does not result in better pay for the typical worker (Schwellnus et al. 2017). At the same time, the ratio of the median wage to the average wage is declining. This is a typical indication for income inequality and reflects the rising wages of people at the top of the income distribution. The war for talent increases both the inequality between social classes and between societies. For example, ICT professionals are often trained in low-income countries, but these countries are unable to retain them because they tend to emigrate to stronger economies with higher wage levels (Zhu et al. 2018).

Alongside these trends, a new digital labor market is on the rise and requires ethical consideration: crowdworking on online platforms. Crowdworkers work on-demand for various clients on online platforms such as Amazon Mechanical Turk (MTurk) and perform tasks of various types and scopes (De Stefano 2015). Crowdworkers are not employed by the platform or the client but work as independent contractors. Hence, they do not receive any social, health or insurance benefits through their online labor (Ettlinger 2016, Fuchs and Sevigniani 2013, Hara and Bigham 2017, Zyskowski et al. 2015). Lack of regulation of on-demand digital labor market and protection of workers' rights threaten key pillars of society, including healthcare systems, retirement pensions and value of education (Morrar et al. 2017).

In other respects, too, the fourth industrial revolution is characterized by the platform economy. This includes peer-to-peer platforms with digital business models such as Amazon, Airbnb and Uber, on which users can offer, share or access products on demand, and information-intensive companies such as Google, Salesforce and Facebook. The high capital value of ICT companies is no longer based on material goods or manufactured products, but in particular on the accumulation of massive amounts of data (Morrar et al. 2017). These vast amounts of data unlock valuable knowledge about markets, customers, and members of society, further enable the personalized application of innovative technologies such as chatbots and image recognition. Available data not only include demographic information, but also locations, banking information, diets, social circles, preferences, and actual user behavior (e.g., Lepri et al. 2017). Big data represent a significant competitive advantage and value for businesses—but is unevenly distributed across industry (World Bank 2021). For example, in 2019, only six companies accounted for more than 40% of worldwide internet traffic (Sandvine 2019). Figure 1 summarizes the internet traffic allocation.

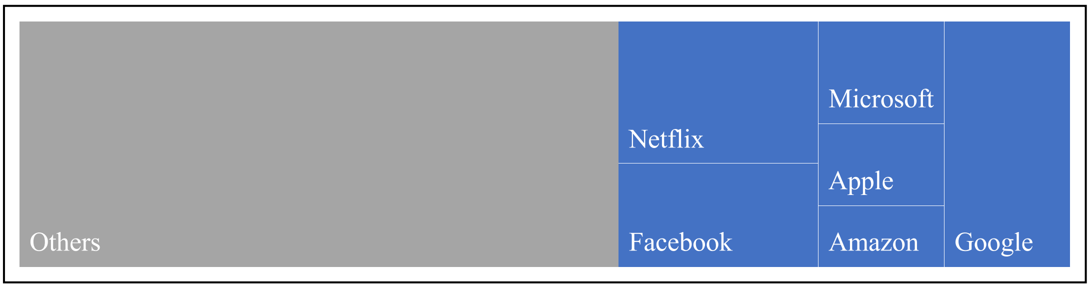


Figure 1. Allocation of worldwide Internet traffic. Modified from World Bank (2021, p. 99) based on data from Sandvine (2019).

The rise of the platform economy and the uneven distribution of data are currently leading to a restructuring of markets. Markets are concentrating a few large players, some of which are even developing into oligopolies and monopolies (e.g., Fukuyama 2021, Rikap 2021). The economic battle for data poses a new threat to members of a society. In an economy in which information about people may be worth more than physical goods, the protection of individual privacy rights and the consequences of privacy violations must be completely rethought.

Today, the fourth industrial revolution is an ongoing process. Like previous revolutions, it harbors social opportunities and risks, leaving it questionable whether the positive socioeconomic consequences will outweigh the negative ones (Luppicini 2012). What makes this revolution special is its broad disruptive power in all areas of societies and individuals' daily lives. Its broad impact makes it all the more important for scholars, politicians, industry representatives and civil society to guide current progress in order to exploit the potential of data and new technologies for social, environmental and economic sustainability. For a social design in which data and innovation specifically promote social welfare, a designated concept is currently evolving—the Society 5.0.

2.2 Society 5.0

Society 5.0 is a rather new concept. It was first launched in 2016 by the Japanese government as part of the Science and Technology Basic Plan (Cabinet Office 2016), the equivalent of the German federal government's High-Tech Strategy 2020 Action Plan. The report specifies the Society 5.0 in several sections and includes underlying challenges such as cyber security, environmental disasters, and energy and data governance.

The basic vision of a Society 5.0 is a continued development of Industrie 4.0, but in pursuit of social welfare: innovative technologies are to be mobilized for social, economic and ecological sustainability. The concepts of Industrie 4.0 and Society 5.0 overlap in that both focus on innovative technologies, the generation and use of big data, and call for interdisciplinary cooperation between academia, government, industry and civil society (Deguchi et al. 2020). The key difference is that Industrie 4.0 focuses on manufacturing and smart factories, while Society 5.0 considers society as a whole. In Industrie 4.0, technologies were used to optimize industry and production. Humans in Society 5.0 are now supposed to benefit from these technologies, making Society 5.0 a so-called "super-smart society" (e.g., Cabinet Office 2016, Deguchi et al. 2020). The premise is our current information society, implying that data from the real world are collected, digitally processed, analyzed, and output such as recommendations or knowledge is supplied back to the real world. Today, services, technologies and devices already operate according to this cyber-physical principle, but often in isolation without communicating with each other. In Society 5.0, a decentralized network is to be formed from all these independently operating systems that collect data, generate output, and pass both on not only to the real world, but also to all other systems in the network. This way, a holistic cyber-physical space will emerge. In other words, just as data from production processes are modeled and optimized in cyberspace in the case of smart factories, this process shall now be transferred to the optimization of all environmental, economic and social areas—creating a super-smart society. Table 2 summarizes Society 5.0's core ideas and how they differ from Industrie 4.0.

Table 2. Industrie 4.0 vs. Society 5.0

	Industrie 4.0	Society 5.0
Design and Origin	• High-Tech Strategy 2020 Action Plan for Germany	• 5th Science and Technology Basic Plan
Objectives and Scope	• Information Society • Focus on manufacturing • Reduction of costs, increase of efficiency	• Super-smart Society • Focus on sustainability • Increase of welfare and well-being
Instruments and Activities	• Cyber-physical systems (CPS) • Internet of Things (IoT) • Mass customization	• High-level convergence of cyberspace and physical space • Balancing economic development with resolution of social issues

Source: Modified from Deguchi et al. (2020).

The aspiration for a Society 5.0 is in line with the 17 UN Sustainable Development Goals (SDGs). These goals concretize the complex concept of sustainability in terms of its various facets and break it down into 169 specific targets (UN 2021a). The SDGs are a central part of the 2030 Agenda, which was formally recognized by the members of the UN in 2015 in order to ensure the sustainable development of the world (UN 2021b). The SDGs capture environmental (e.g., SDG 13, "Climate Action"), as well as social (e.g., SDG3, "Good Health and Well-being") and economic (e.g., SDG 8, "Decent Work and Economic Growth") aspects of sustainability. Sustainability and the well-being of individuals are an equally central component of Society 5.0. The Society 5.0 concept does not complement or modify the SDGs themselves but focuses on the particular potential of data and technology in measuring and promoting the SDGs. For example, while SDG 12 ("Responsible Production and Consumption"), specifies the direction in which efforts should be guided, in a Society 5.0, data and technology would be part of the goal's specific advancement: data provide information on the carbon footprint of products, where unnecessary production waste occurs, and what wages are paid along the value chain, data-driven technologies optimize production processes in terms of energy efficiency and waste management. The unique potential of data in addressing the SDGs is not only reflected in the lively research on this topic, but in the report A World That Counts (2014), in which the UN itself explicitly called for the mobilization of data to promote sustainable development. Society 5.0 is a model of society in which central problems have been solved by means of innovation.

Already today, during the fourth industrial revolution, concrete approaches to the use of data and technology for sustainability emerged and mark the beginnings of a Society 5.0. For example, in form of technology-based social innovations, i.e., new approaches—products, services, laws, technologies or businesses—that address social issues and increase well-being (Abbott 2014, Hahn and Andor 2013, Marolt et al. 2015). Specific examples include areas such as urban planning, public health or infrastructure.

In urban planning, smart energy supply concepts are on the rise. Smart grids are designed to meet the growing energy needs of our society with the help of renewable energies (Ak et al. 2016). Smart grid is a data-driven system that uses machine learning to respond flexibly to different energy demands in a virtual auction (Zhang et al. 2018a). It thereby creates a stable energy supply, which is one of the biggest obstacles to the introduction of renewable energies such as wind power or photovoltaics (Zhang et al. 2018b). Smart homes further contribute to optimizing the energy demand of buildings and conserving resources (Strengers and Nichols 2017). In addition, data-based homes aim to improve their residents' quality of life, e.g., by enabling elderly people to live longer in their own homes using wearable sensors, security systems and detection of abnormalities (Deen 2015, Ehrenhard et al. 2014, Majumder et al. 2017). Other data-driven technologies are improving public health. For example, mobile data can measure disease transmission (Tizzoni et al. 2014), behavioral data allow to assess and promote mental health outside of clinical stays or even detect emergencies (De Choudhury et al. 2013, Matic and Oliver 2016). Concerning infrastructure, technologies help to avoid traffic jams and thus minimize wasted energy and time (Deguchi 2020). Examples include autonomous navigation systems, which help drivers react to changes in their environment in real time. Further, autonomous vehicles are expected to significantly reduce both dust pollution and the number of accidents. Similar approaches exist for cabs and rail transport.

At this point, Society 5.0 is a vision. It remains uncertain whether and when it will actually turn into reality. However, as the fourth industrial revolution is currently developing far beyond a pure focus on production processes, Society 5.0 serves as a valuable basis to reflect on how we can harness potentials and where we can guide technologies in order to approach a human-centric and sustainable world.

Chapter 3

Citizen Data as an Enabler of Society 5.0

3 Citizen Data as an Enabler of Society 5.0

The transformation of a society into Society 5.0 requires one key ingredient: data. The UN rates data as "the lifeblood for decision-making and the raw material for accountability" (UN 2014, p. 2). The importance of data for technological progress is as broad as its potential applications for socio-ecological sustainability, e.g., for modeling a cyber-physical world, for operating technologies such as smart grids and autonomous navigation systems, for containing pandemics, for quantifying poverty and living conditions, or for training algorithms. A universal definition of data is correspondingly difficult. From a rather technical perspective, data are „the physical representation of information in a manner suitable for communication, interpretation, or processing by human beings or automatic means“ (OECD 2006, para. 2). In its contextual understanding, this dissertation follows the description of the UK National Data Strategy as information about things, systems and people (DCMS 2020): the term data refers to information from the growing IoT, describing, for example, places in the form of geospatial details and our environment based on weather and biodiversity. Data about people is information about individuals such as behavior or identities, but also includes social details such as demographics.

Without comprehensive and qualitative data, there will be no super-smart society. This central role of data poses various challenges. These must be resolved as we aim to transform our society into Society 5.0 in order to avoid turning utopia into dystopia. How to ensure that individuals benefit from their disclosed data and are not discriminated or surveilled? How and where to generate data in order to fill data gaps and thus include all members of society equally? To better understand how a human-centric, data-driven society may be built, the remainder of this chapter reflects on ethical challenges to consider and on civic participation as part of a corresponding approach to address selected challenges.

3.1 Ethical Challenges of a Data-driven Society

Violation of Privacy Rights. The collection and algorithmic analysis of data imply various social, ethical, and legal dangers for individuals. Dangers include the general violation of individual rights to privacy. Privacy of data means that the individual has control over whether and what data about him or her are disclosed (Bélanger and

Crossler 2011), how data are collected, processed and used as well as who has access to it (Smith et al. 1996). The misuse of data can have extreme societal impact, as the data-driven manipulation of the 2016 US election known as the Cambridge Analytica scandal highlighted (e.g., Heawood 2018, Hinds et al. 2020). Privacy breaches do not only involve data that have actually been shared by a person. Algorithmic analyses also facilitate the generation of new insights about individuals by combining existing data sets. For example, social media activity patterns can lead to conclusions about mental illness or sexual orientation without this information having been specifically shared by a person (De Choudhury et al. 2013, Kosinski et al. 2013). Data privacy must be a fundamental and protected right in a socially desirable super-smart society.

Accountability of Algorithms. Algorithms lack transparency and accountability (e.g., Kroll et al. 2016, Lepri et al. 2017, Pedreschi et al. 2019). Generally, self-learning algorithms aim to optimize certain outputs according to predefined criteria. However, how exactly an algorithmic model optimizes an output according to these criteria, and how those criteria may automatically change over time, is mostly a black-box (Pedreschi et al. 2019). This lack of insight leads to ethical challenges, especially when algorithmic outputs have real-world consequences, e.g., when outputs are used to make decisions about lending, recruiting personnel, or controlling self-driving cars (Lepri et al. 2017). Both development and use of algorithms require trust in the technical model as there is no possibility of insight and verification. Yet, for example, EU citizens have had the right to obtain the underlying logic behind automated decisions since 1995, and this right remains valid in the European Union's General Data Protection Regulation (GDPR) of 2018 (European Commission 2016) (see Wachter et al. 2017). Even assuming that the black-box of algorithms could be opened, another challenge arises around the question of who would be held legally responsible for illegal or normatively undesirable decision-making logics. After all, algorithms do not constitute a legal entity (e.g., Abdul et al. 2018, Kroll et al. 2016).

The lack of transparency and accountability is further a constraint because algorithmic outputs may be socially discriminating. An unequal treatment of different societal groups in algorithmic outputs can arise in several ways (Lepri et al. 2017). First, an algorithm might overweight individual criteria according to which it optimizes output. If, for example, a targeting process assigns too much statistical weight to an individual's zip code, members of precarious neighborhoods with low incomes could easily be assumed to have a propensity to commit crime (Christin et al. 2015). In another example, individuals' dispo limit was not assessed based on actual payment history, but on the stores the individual shopped at (Ramirez et al. 2016). Second, undesirable results may arise when developers use algorithmic models that are inappropriate for a specific study context (Calders and Zliobaite 2013) or when a user applies an algorithm in a particular way in making decisions that reflects his or her personal biases, e.g., by filtering in the output only for certain content such as skin color (Diakopoulus 2015).

Biased Data. Data are the driver of technological progress and pose a particular social and ethical threat. For example, data are used both to train algorithmic models themselves and as input for processing by already trained algorithms in order to derive output such as knowledge and recommendations (Aggarwal 2015). Although data are a core component of both statistical learning and follow-up analyses, their quality is still insufficient: data contain critical biases and gaps (World Bank 2021). Biases in data sets can arise because prevailing biases in society are correctly measured and thus unreflectively included in the data set (Lepri et al. 2017). Prevailing social biases may include stereotypes, racism, and unequal treatment. Consequently, algorithms trained with biased data will, perceive existing social discrimination against individual groups in data as a correct pattern and will therefore continue to apply this pattern when generating future output (Barocas and Selbst 2016, Crawford and Schultz 2014, Ohm 2010). Such discriminatory pattern may be that decision makers have historically classified minorities as less creditworthy, guiding the algorithm to adopt minority membership as a criterion for low creditworthiness.

Problematic data gaps exist even in simple surveys such as censuses, even though they are conducted with the motivation of being representative of society (World Bank 2021). Estimates suggest that censuses missed between 170 and 320 million people in 2013, and that these include the poorest communities, such as the homeless, nomads, and slum dwellers (Car-Hill 2013). The corona pandemic, too, highlights insufficient quality of data. Of 190 countries surveyed in 2020, less than half differentiated between men and women in their reported COVID-19 data (World Bank 2021).

Building on data that are incomplete or in which certain characteristics are underrepresented, algorithms are likely to optimize their output disproportionately for those groups that have already been prioritized during data collection, e.g., white males (Glauner et al. 2018, Podesta et al. 2014). This way, existing unequal treatments of social groups, countries, and regions reflected in data will be reflected in future outputs and decision-making as well, both when a model is trained with that data and when an algorithm or person uses that data to derive decisions. A scandal in 2015 involving Google provides a vivid example (Curtis 2015). A designated function in the Google Media Library automatically tagged images with their content in order to facilitate the search. The corresponding algorithm was probably trained with a data set in which black people were underrepresented. As a result, several black people claimed to have been recognized by Google as gorillas. Inequality due to gaps and low data quality not only exists within, but also between societies and economies. Especially in data on low-income countries, there are massive gaps in information on population and local conditions. Data record only 22 percent of civil registrations, births and deaths in low-income countries (World Bank 2021). In rich countries, on the other hand, 95 percent are. Worldwide, the identity of around one billion people is not captured in any data at all (Desai et al. 2018). The discrepancy in the availability of geospatial data such as maps and postal codes is similarly large between high-income and low-income countries. In order to create a society that is not only super-smart, but—in line with Society 5.0—ensures well-being for all members equally, there must be complete and qualitative data.

3.2 Civic Participation in Data Governance

3.2.1 Data Ownership and Management: User-centric Models

The ethical challenges in building a Society 5.0 are manifold. Their addressment is correspondingly complex but will inevitably involve the management of data. Data governance describes efforts to manage data in a way that enhances their quality and value (Otter and Weber 2011). The specific actions of data governance depend heavily on the context, but usually involve the explicit distribution of decision rights and duties. Data Governance in public interest suggests distributing more rights to the individual. Indeed, researchers are currently proposing a corresponding approach that allows to protect individual privacy rights while increasing public intent data quality:

user-centric models for personal data management (e.g., Garcia-Font 2020, Lepri et al. 2017, Qiu et al. 2019, Solodovnikova and Niedrite 2011). The main objective of these models is to give individuals control over their generated personal data throughout the full data lifecycle (Pentland 2012). Such data may include locations, passwords, health data or other information recorded by mobile devices (Lepri et al. 2017). While data management models have previously allowed profit-oriented service providers in particular to manage information about users, they now increasingly allow users to manage their data and access of service providers as well (Jøsang and Pope 2005).

The Personal Data Store (PDS) is an exemplary implementation proposal for such user-centric data management model (Guidotti et al. 2015). This store displays various data about a person in an easy and concise manner. Besides data, the PDS also shows personalized suggestions based on selected data sets as well as industry-standard analysis results, e.g., shopping behavior or risk of illness. Each user manages his or her own PDS and gets to decide with whom and in which format he or she wants to share data. E.g., instead of sharing raw data, an individual could also share an aggregated or anonymized data format. Using the PDS, a user is in charge whether he or she is willing to take a privacy risk by sharing his or her data with specific service providers.

Another hands-on approach mobilizes blockchain technology to implement a user-centric data management model (Zyskind and Nathan 2015). Blockchain uses a publicly verifiable open ledger, thereby enabling users to distribute information decentrally and without an intermediary within a network (Nofer et al. 2017). This information can also refer to an individual’s personal data, which he or she can thus manage and share securely within a network (Zyskind and Nathan 2015). A particular advantage to this approach is that regulations and laws can be embedded in the blockchain itself, automatically preventing their non-compliance. The Enigma[6] platform, developed at MIT in 2015, is a practical implementation of such blockchain-based data management model. Simply put, Enigma's so-called Secret Network[7] securely stores user data and, after access permission from a user, allows third parties

[6] https://www.enigma.co
[7] https://scrt.network

to use selected and anonymized data sets for analysis, computing and algorithm training. Thus, while several parties can use the data and realize its potential, the data are kept within the Secret Network without being ever transferred or stored on third-party servers.

The introduction of EU citizens' right to portability of their data according to the GDPR paves the way for establishing user-centric models in practice (European Commission 2016, De Hert et al. 2018). This right to portability considers data digital property and recognizes the user as the legal owner of his or her own data. The legal entitlement of users to view and manage their data in designated databases may further lead to an increasing decentralization of data. Because private organizations in particular manage user data in a centralized manner, they have the power to accumulate large amounts of data and create economic value. If every user manages access to his or her data in a decentralized manner, new competitive pressure can arise on service providers and platforms, thus counteracting monopolization (Guidotti et al. 2015).

3.2.2 Data Sources and Quality: Citizen-generated Data and Civic Data Sharing

Complete and high-quality data are the foundation of Society 5.0. A common framework for evaluating data quality are the four V's, i.e., volume, variety, velocity and veracity (e.g., Hu et al. 2014, Rubin and Lukoianova 2013, Schroeck et al. 2012). Volume refers to the massive amount of unstructured data so that it can be processed by algorithms. Variety refers to the variety and diversity of sources from which data are obtained. Velocity refers to the timeliness of data so that generated insights are immediate and relevant. Veracity refers to the quality of data, taking into account factors such as trustworthiness, structure, and contextual fit. For data meant to be used in alignment with the SDGs, the World Development Report (World Bank 2021) has established distinct, more detailed evaluation criteria. Table 3 summarizes the criteria. There are extensions to the four V approach in the sense that it also includes coverage of all societal groups and privacy protection as additional quality criteria. For example, insufficient fulfillment of the granularity criterion may be that data are not broken down to the gender level. Low granularity might lead to an overrepresentation of men in mean values or to a lack of insight on how genders differ on certain criteria. Data sets that fail to adequately meet these criteria not only lead to error-prone outputs and technologies, but also imply socially undesirable effects that contradict a Society 5.0.

Table 3. Quality Criteria for Data

Data have adequate coverage	**Data are of high quality**	**Data are easy to use**	**Data are safe to use**
Completeness	Granularity	Accessibility	Impartiality
Timeliness	Accuracy	Understandability	Confidentiality
Frequency	Comparability	Interoperability	Appropriateness

Source: Modified from World Bank (2021, p. 55).

There are distinct data types that differ in their ownership, quality characteristics, and weaknesses. The World Development Report (World Bank 2021) proposes a two-dimensional framework for the categorization of data types. The first dimension of the framework reflects how data are collected. It differentiates between traditional and modern methods. While traditional methods such as surveys are expensive and time-consuming, new methods such as satellite imagery and sensor data generate more and higher quality data in less time. The second dimension of the framework reflects the purpose and ownership of each data type: public intent data and private intent data. Public intent data are collected with the specific aim of benefiting society by depicting it and thus supporting decisions, e.g., by politics and research. Private intent data, on the other hand, include all data collected for commercial purposes, in particular by the private industry. This distinction is central, as each type of data implies advantages and disadvantages for its use in promoting Society 5.0.

Public intent data are of high quality as they are collected in an effort to cover the population in a representative and complete manner (World Bank 2021). Moreover, the sources of the data are usually known and trustworthy. The methods used to collect public intent data are increasingly modern, e.g., surveys are less conducted with paper and pencil and more digitally, and data are extracted from e-government platforms. However, many public intent data collection efforts are still far too irregular, expensive and time-consuming (Kilic et al. 2017, Serajuddin et al. 2015). Therefore, while the representativeness of public intent data does not fail due to intention, it fails due to severe constraints in data collection methods. Public intent data are therefore usually inferior to private intent in terms of volume, variety and velocity.

Private intent data primarily originate from the use of modern information technology such as mobile devices, sensors and the Internet in people's everyday lives (World Bank 2021). As the type and use of information technology increases rapidly, so does the volume of private intent data, which, unlike public intent data, are technically suitable for analysis, training algorithms and operating data-driven technology. However, the potential of private intent data to promote a Society 5.0 remains unused for two reasons. First, private intent data are not collected aiming at representativeness, hence leading to a high risk of biases, e.g., because poor population groups produce less data. Second, private intent data are collected and processed to increase profit, often neglecting their corresponding effects on social welfare.

Today, there are data that strive for representativeness, completeness and minimal biases, but whose quality is limited by their method of collection (public intent data). And there are extensive, timely, and diverse data sets that contain biases and are used for purposes other than social welfare (private intent data). How can we govern these data to overcome their shortcomings and exploit their benefits for sustainability in the line with Society 5.0? Various approaches are conceivable, including the optimization of collection methods, regulation of data ownership or government access to private data. This dissertation proposes an approach that seems particularly promising in light of the ethical challenges on the road to Society 5.0: the active participation of civil society in improving data availability and quality.

Civic participation appears to be particularly useful in two regards. First, citizens can help to optimize and facilitate the collection of public intent data in order to improve data quality in line with the data quality criteria presented in Table 3. Literature considers this approach as “citizen-generated data.” Second, citizens can share private intent data in order to complement public intent data, to reduce biases and support social welfare. This dissertation newly introduces this approach as “civic data sharing. Figure 2 picks up the framework of data types (World Bank 2021) and illustrates this dissertation’s proposal on how the public can participate in increasing data quality based on those two approaches.

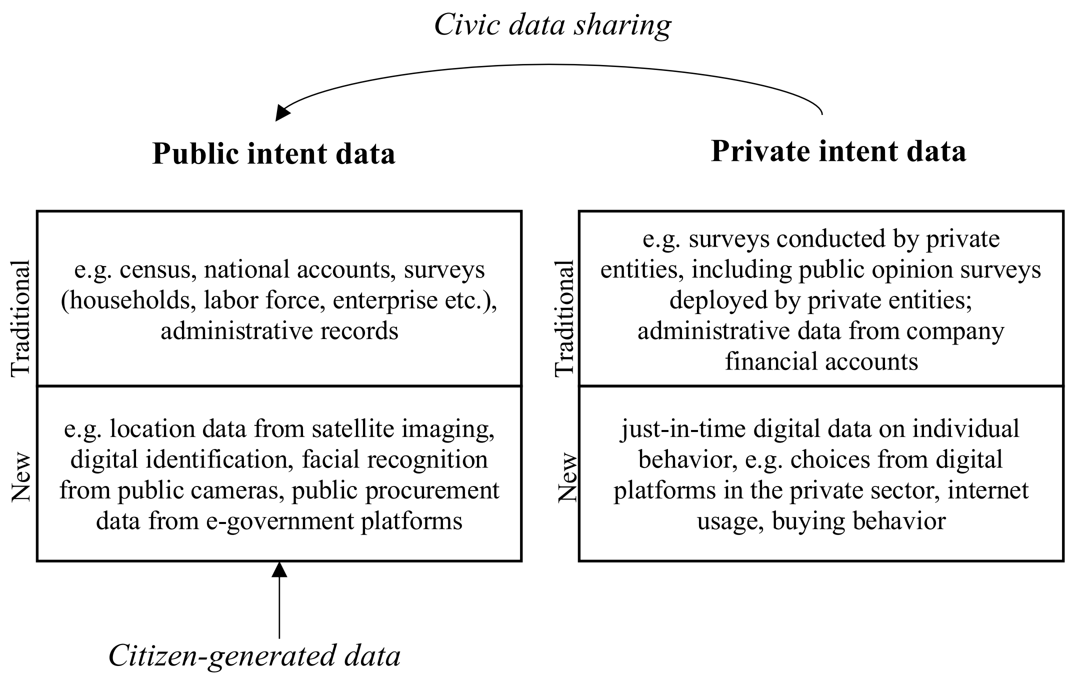


Figure 1. Proposal of civic participation approaches to improve public intent data quality. Underlying framework of data types modified from World Bank (2021, p. 28).

Citizen-generated Data. Publicly owned data to promote Society 5.0 can be generated not only by third parties such as government or academia, but also by individuals. The active generation of data through the participation of civil society has gained attention in research and practice alike and is commonly referred to as citizen-generated data (CGD) (e.g., Gray et al. 2016, Lämmerhirt et al. 2018, Maskell et al. 2018, Meijer and Potjer 2018, World Bank 2021). Broadly conceptualized, CGD are data that are proactively collected by citizens so that their perspectives and needs are represented in data that shape decisions and policy measures (CIVICUS-DataShift 2017, World Bank 2021). The specific scope of the term is diffuse in that there are comparable concepts which emphasize particular characteristics in their understanding of CGD, e.g., citizen science, crowdsourcing, and social accountability (Lämmerhirt et al. 2018).

Both the role of citizens and the method of data generation can vary widely. For example, existing data can be enriched or supplemented, completely new data can be created, or unstructured data can be formatted (Lämmerhirt et al. 2018). Citizens' methods include classifying and tagging data or generating data through sample collection or documentation. In some cases, citizens also rely on digital tools or devices from private industry, e.g., when they install sensors or upload data into existing software (World Bank 2021).

In their report, Lämmerhirt et al. (2018) present several case studies that illustrate the contribution of CGD in promoting SDGs in line with Society 5.0. One advantage of CGD is that it can include data that would have been too costly and laborious to collect without civic assistance. In Canada, for example, measuring water quality and water traffic is very costly due to the sheer size of the country. The responsible organizations therefore launched a campaign in which citizens could voluntarily engage in the regular documentation of water quality in their area (Carlson and Cohen 2018). To this end, citizens were provided with digital tools and software both to measure parameters such as pH and dissolved oxygen and to submit them to an open access data hub. The gathered data significantly supported the Canadian government in guiding policy decisions for climate and environmental protection addressing SDG 6 ("Clean Water and Sanitation") and SDG 12 ("Responsible Production and Consumption").

Another case study shows how CGD can support mapping populations in disadvantaged regions into existing data, thereby reducing gaps and biases. In Indonesia, protecting society from natural disasters is an important challenge. In order to plan cities and assess the risk of potential disasters, authorities require accurate data on locations and numbers of buildings, and other infrastructure. National authorities lack permission to map all, especially rural, parts of the country. And even in urban areas they often simply lack the capacity for detailed mapping. To overcome these hurdles, a CGD initiative in cooperation with disaster control organizations was launched and encouraged Indonesian citizens to support data collection: volunteers used diverse sources such as analog maps, GPS data, and satellite imagery to add to the existing database in OpenStreetMap[8]. They commented and edited the newly generated mapping information online. As a result, the risk exposure software produced better risk predictions of environmental disasters through optimized data and

[8] OpenStreetMap is a non-profit, free wiki world map that can be edited by anyone; https://www.openstreetmap.org./

thereby promoted SDG 11 ("Sustainable Cities and Communities"). Data have been improved particularly for people with lower incomes as buildings in sub-district areas are now included to a greater extent.

However, citizens do not only contribute to social welfare by producing data on their surroundings, the environment or other people. Voluntary documentation of their own behavior can likewise positively impact both individual and societal utility. Self-monitoring mobile apps allow users to easily enter their behavioral data and thereby monitor it digitally. The goal of digital self-monitoring usually is to motivate behavior change and to thereby increase a user's well-being (e.g., Bakker and Richard 2018, Turner-McGrievy et al. 2013). Current apps cover anticipated behavior changes concerning climate and environmental protection[9], retirement savings[10], mental health[11], weight loss and physical fitness[12]. As the goals vary, so do the data that users generate about themselves while using the app.

The use of self-monitoring apps can improve the individual and social well-being while supporting SDGs. For example, the rising rate of depression worldwide is an increasing burden on the quality of life (World Health Organization 2020). Yet traditional forms of therapy reach only a fraction of those who are suffering or at risk, because people do not seek help and the capacity to provide it is limited (e.g., Australian Bureau of Statistics 2007). The documentation of behavioral data based on cognitive behavioral therapy enables better management of anxiety (e.g., Huppert et al. 2006) and initial treatment of post-traumatic stress (e.g., Ehlers et al. 2003). Thus, using self-monitoring apps can not only improve an individual's mental health, but also stabilize health care systems according to SDG 3 (“Good Health and Well-being”).

Data generated with self-monitoring are not distinctively CGD. Although many behavioral changes motivated by self-monitoring apps are in public interest, app providers are usually part of private industry. According to the data type framework of the World Development Report (World Bank 2021), data disclosed to the private industry are considered private intent data, which are likely to be additionally used for

[9] E.g., https://www.klimakarl.de/
[10] E.g., https://www.monkee.rocks./
[11] E.g., https://www.headspace.com/
[12] E.g., https://www.freeletics.com/de/

commercial purposes and to imply a privacy risk. However, self-monitoring apps enable large segments of society to generate new data that promotes social welfare, which qualifies them as a valuable tool for generating CGD—especially if offered by welfare-oriented organizations in future.

Civic Data Sharing. Another approach to increasing public intent data quality is to supplement it with private intent data. Although vast amounts of qualitative private intent data exist, their social benefit will not be activated if the data are used primarily for commercial purposes. By sharing private intent data for collective benefit, they can have particular value for the SDGs. Private intent data is much more timely, granular, and in some cases less biased because it reflects actual behavior (Salganik 2019). This way, private intent data can typically reveal larger and more detailed information that are better suited to support policy decisions among others. However, it is important to bear in mind that private intent data is not representative of societies and can therefore only be evaluated in combination with public intent data. As the use of mobile devices and the Internet is increasing not only in industrialized nations but also in developing countries, the hurdle of representativeness is becoming increasingly smaller (World Bank 2021).

Data can be shared on different hierarchy levels, such as on an institutional level, on a local or international level, in a centralized or decentralized way (Chawinga and Zinn 2019). During the 2020 corona pandemic outbreak in Germany, for example, a private telecommunications company, Deutsche Telekom, transmitted the mobile data of several hundred thousand people to a research institute to better evaluate movement patterns (Tagesschau 2020b). Other researchers used cellphone-recorded data not only to measure the time citizens in Mexico, Colombia, and Indonesia spent on average in their homes, but also published differences in mobility behavior between poor and rich populations (Fraiberger et al. 2020).

Yet when the private industry shares their customers' data among third agents to increase social welfare, a moral paradox emerges. While society as a whole benefits from the value of its data, as in the protection of public health, the individual's fundamental right to privacy is compromised (Taddeo 2017). However, just as citizens can generate new data themselves, they can also share existing private intent data. The distinction between CGD and sharing private intent data is that data is not consciously produced or documented by citizens. Rather, individuals use various services, devices, or applications in their daily lives, which automatically produce large data volumes as a byproduct of their interaction. In line with the concept of user-centric data management model, individuals should not only have control over parties and purposes for which data access is denied, but also over parties and purposes for which data is proactively shared. If individuals can decide for themselves whether they are willing to take a privacy risk for the benefit of the general public and share their data, two positive effects arise. First, public intent data is complemented, activating the potential of the data for social welfare, and second, the moral paradox is solved because data sharing is in line with individual preferences on the trade-offs between risks and potentials. To continue the corona pandemic example: In Germany, the government introduced a voluntary mobile app, the Corona Warn App[13]. The app does not record the location of its users but tracks whether a user has been near a person infected with the corona virus based on Bluetooth connections. In doing so, it is up to citizens to decide whether they want to download the app, enable Bluetooth contact tracking, and store their test results in the app. Thus, the individual decides if he or she wants to share certain data sets about him or herself for the benefit of public health.

[13] https://www.bundesregierung.de/breg-de/themen/corona-warn-app

Chapter 4

Studies on Civic Data Mobilization: Sharing Behavior and CGD Technology

4 Studies on Civic Data Mobilization: Sharing Behavior and CGD Technology

Data governance covers several domains, including aspects of data ownership, data management, and data quality, which are outlined in the previous chapter of this dissertation. Each of these domains imply potential measures that can contribute to solving the challenges of a data-driven society and to increase welfare in line with Society 5.0. This dissertation comprises three papers, which aim to expand knowledge on data quality enhancement measures in particular. By involving citizens in collecting and sharing personal data, civil society obtains the power to improve data quality and to shape data in its own interests. All three papers of this dissertation address the mobilization of citizen data for Society 5.0. The papers differ in their methodology and focus. While Paper I and Paper II contribute knowledge on how to organize the sharing of private intent data in a way that citizens find appropriate and that avoids ethical concerns, Paper III contributes knowledge on how to guide innovative technologies to promote social welfare, providing a use case on how to fill data gaps by facilitating CGD. Figure 3 provides an overview of the context in which each paper examines civic participation to improve data quality.

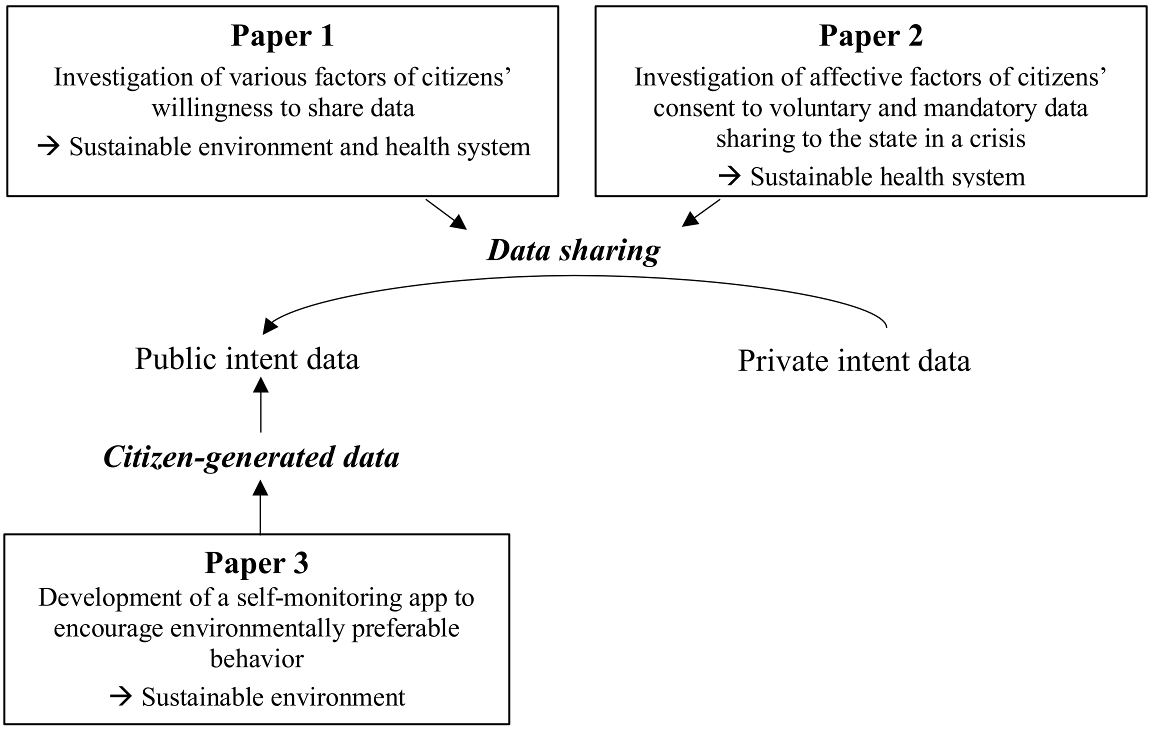


Figure 2. Mapping of dissertation papers to approaches of civic participation to improve the quality of public intent data.

Paper I titled *The Social Dilemma of Big Data: Donating Personal Data to Promote Social Welfare* (by Kirsten Hillebrand and Lars Hornuf) investigates several factors that drive individuals' willingness to share private intent data to a database that promotes social welfare. While society at large could benefit from the database, each individual has an incentive to deviate from disclosing his or her personal data to the database, because data disclosure comes with personal privacy risks. Individuals might thus freeride on the contributions of others, constituting a social dilemma. By conducting an online experiment with US citizens, Paper I investigates how the willingness to donate personal data to a database changes with the risk of data getting leaked, the data-driven technology's impact on social welfare, the organization that manages the database to operate technology, and a potential human component of the technology's underlying algorithm. The paper compares two domains of social welfare: a sustainable environment and a sustainable health system.

Paper II titled *The Role of Fear and Trust when Disclosing Personal Data to Promote Public Health in a Pandemic Crisis* (by Kirsten Hillebrand) investigates affective and situational factors that drive individuals' consent to disclose their private intent data to the state. During the onset of the corona crisis, many states implemented sudden data collection measures without prior public discussion, which may raise ethical considerations because individual preferences may change when experiencing fear. Conducting an online experiment with German citizens, Paper II investigates how civic consent to data sharing differs when data sharing is voluntary versus when it is legally mandated by the state, and what drives this consent in a crisis. The paper covers the protection of public health, hence a sustainable health system as a domain of social welfare.

Paper III titled *"KlimaKarl" — A Chatbot to Promote Employees' Climate-Friendly Behavior in an Office Setting* (by Kirsten Hillebrand and Florian Johannsen) follows a common design science research procedure to develop a chatbot that allows its users to track their daily behavioral data and to improve their carbon footprint. The chatbot is part of an iOS and Android mobile app designed in particular to sensitize office employees towards more climate protection during their everyday job activities. The usability of the mobile app is tested with employees from two pilot companies as part of a CO_2-saving competition. The paper addresses the promotion of a sustainable environment as a domain of social welfare.

4.1 The Social Dilemma of Big Data: Donating Personal Data to Promote Social Welfare

Abstract. When using digital devices and services, individuals provide their personal data to organizations in exchange for gains in various domains of life. Organizations use these data to run technologies such as smart assistants, augmented reality, and robotics. Most often, these organizations seek to make a profit. Individuals can, however, also provide personal data to public databases that enable nonprofit organizations to promote social welfare if sufficient data are contributed. Regulators have therefore called for efficient ways to help the public collectively benefit from its own data. By implementing an online experiment among 1,696 US citizens, we find that individuals would donate their data even when at risk of getting leaked. The willingness to provide personal data depends on the risk level of a data leak but not on a realistic impact of the data on social welfare. Individuals are less willing to donate their data to the private industry than to academia or the government. Finally, individuals are not sensitive to whether the data are processed by a human-supervised or a self-learning smart assistant.

4.1.1 Introduction

In this study, we examine several factors that encourage individuals to provide personal data to a database that promotes social welfare. Modern data-driven technologies have the potential to improve the well-being of ordinary citizens in various domains of life. Organizations have implemented these technologies, for example, through smart assistants, augmented reality, and robotics. Individuals who benefit from these technologies provide sensitive and valuable data to academia, the government, and the private industry. Firms can generate additional profits using these data. By making their data available, individuals may, however, also support organizations that promote social welfare. The UN (2014) has publicly called for the mobilization of individual data and initiated a global data partnership (www.data4sdgs.org) and database (https://www.sdg.org/#catalog) to promote environmental and social sustainability. Yet the available data for digital technologies still need improving. As the Global Partnership for Sustainable Development Data (2020) notes, whole groups of people and important aspects of their lives are still not captured digitally. More diverse, integrated, and trustworthy data could lead to better decision making and real-time citizen feedback that has the potential to promote social welfare.

The necessity to mobilize individual user data has recently become omnipresent in the context of governmental policies to fight the COVID-19 pandemic. Various countries around the world have developed and implemented tracking apps that use personal infection and location data to help control the spread of the virus and to protect public health (e.g., Germany: Corona-Warn-App; South Korea: Corona 100m; US: Care19 and Healthy Together). Other examples in which the mobilization of individual user data can promote social welfare include the tracking of human migration to ensure medical support during an earthquake (UN 2021) and the tracking of deforestation combining satellite imagery and citizen-generated data (UN 2020). In the future, data mobilization will become technologically feasible in ever more scenarios and increasingly relevant because of the simultaneous increase in data availability and global challenges such as migration and climate change.

Data donations not only are beneficial to society but also, unfortunately, constitute a social dilemma. While society at large could benefit from data donations, each individual has an incentive to deviate from donating personal data, because data donations come with personal privacy risks. Individuals might thus freeride on the contributions of others. If not enough people donate their data, the respective database is not usable to operate a data-driven technology, and everyone is worse off than had they cooperated and donated their data. In other words, if enough people donate their data, a public good emerges: a database large and diverse enough to operate data-driven technology to increase social welfare. Regulators therefore need to introduce efficient ways to help the public benefit from its own data.

To examine the factors that encourage individuals to provide their data, we focus on smart assistants as a data-driven technology to increase social welfare. Smart assistants can convert large amounts of data into personalized information and help users make socially desirable choices, for example, by selecting relevant information according to consumption patterns and providing tips that are tailored to individual habits and easy to follow. However, to develop and operate such an assistant that offers informed and comprehensive decision support, a smart assistant must have access to a sufficiently large database of diverse, timely, and trustworthy data. Popular examples of smart assistants are Amazon's Alexa and Apple's Siri. Decision-support systems, however, also allow for efficient energy management in households (Kolokotsa et al. 2009). Other examples include big data-based smart farming systems (Wolfert et al. 2017) and clinical decision-support systems that improve health care decisions by providing intelligently filtered information to health care professionals (Musen et al. 2014). In the following analysis, we provide insights into what makes people donate their data to a database that is used to develop and operate a smart assistant to increase social welfare. In an online experiment, we investigate how the willingness to donate personal data (*WDPD*) to a database changes with the risk of data getting leaked and a data-driven smart assistant's impact on social welfare, the organization that manages the database to operate a smart-assistant, and a potential human component of the underlying algorithm of the smart assistant. We compare two domains of social welfare: a sustainable environment and a sustainable health system.

In the past two decades, an extensive literature on the sharing of data has emerged. However, this literature often neglects the social dilemma of data sharing and frequently presumes that data from a single individual alone are utilizable (UN 2014, Cai and Zhu 2015). Our study differs from extant literature because we aim to better understand how individuals donate personal data in a scenario in which the corresponding database must be sufficiently large and diverse to develop and operate a technology that promotes social welfare. To some degree, we thereby contribute to solving the social dilemma of big data and help society benefit from the value of its personal data. The remainder of this dissertation proceeds as follows: in section 2, we relate our research question to existing literature and develop testable hypotheses. In section 3, we describe the empirical implementation of our online experiment. Section 4 presents the data and outlines the empirical results. Section 5 presents a discussion of our findings and concludes.

4.1.2 Theoretical Considerations

Data Disclosure and Privacy. Data can be shared on different hierarchy levels—for example, on an individual or institutional level, on a local or international level, and in a centralized or decentralized way (Chawinga and Zinn 2019). In recent years, data sharing on the individual level has received growing interest by academics and policy makers. This interest, among others, results from citizens generating enormous amounts of data through the increasing use of digital devices and services as well as increasing concerns with data privacy.

Different disciplines have investigated data sharing under privacy risks. Information systems scholars developed the privacy calculus model in the context of technology usage (Dinev and Hart 2006), which has become a well-established concept to investigate data sharing under privacy risks on an individual level. In the privacy calculus model, the term “calculus” refers to the rational cognitive cost–benefit trade-off that technology users face: realizing the expected utility by disclosing personal data versus avoiding the anticipated costs of a privacy violation by not disclosing personal data (Culnan and Armstrong 1999, Dinev and Hart 2006). The individual decision of whether to disclose personal data or not depends on the respective outcome of this cost–benefit analysis. Empirical research evidences that the individual benefits are often perceived as outweighing the costs of privacy risks. Individuals are willing to share their personal data and take privacy risks, for example, to participate in social media networks (Dienlin and Metzger 2016, Choi et al. 2018), to receive financial rewards (Grossklags and Acquisti 2007), to make e-commerce transactions (Dinev and Hart 2006), and to receive personalized content or recommendations (Sun et al. 2015, Kim and Kim 2018). The emergence of the IoT and the use of mobile devices have further accelerated the type of technology that enables data sharing through, for example, smartphones (Keith et al. 2010) and IoT devices such as refrigerators (Kim et al. 2019).

The digital marketing and behavioral sciences literature has extended the rational perspective of the privacy calculus model by examining attitudinal and contextual factors that work as antecedents of individual data disclosure. Factors that complement the cost–benefit analysis of the privacy calculus model include trust (Joinson et al. 2010), anonymity (Pu and Grossklags 2017), sensitivity of information (Mothersbaugh et al. 2012), past privacy experience (Xu et al. 2012), extroversion and attitude (Chen 2013), and social privacy norms (Zlatolas et al. 2015).

Data Philanthropy. In many cases, using digital services with privacy risk equals an exchange of data for personal benefits (Xu et al. 2009). However, as in the case of sharing health data during a pandemic, data can also benefit society at large. How do individuals decide in a cost–benefit trade-off whether they should disclose their personal data to increase *social* welfare rather than their *personal* utility? When individuals rely on the rational approach of the privacy calculus model, they may not find it worthwhile to share their data and risk their privacy to promote social welfare. Nevertheless, individuals might engage in self-sacrificing behavior and disclose personal data, even though it may be rational for them to prioritize the protection of their privacy rights over societal benefits. Such behavior can occur if individuals view data disclosure less as a rational exchange of goods and more as a morally and emotionally motivated donation to a good cause.

Kirkpatrick (2013) first coined the term "data philanthropy" for the donation of data by individuals or profit-oriented organizations without expecting personal benefits in return. The literature on general donation behavior provides important insights into why individuals might be willing to donate their data and take a privacy risk to promote social welfare. De Groot and Steg (2008) and Schwartz (1970) show that individuals might consider a self-sacrifice morally obliging if it helps others or maximizes social welfare. In addition to acting according to one's moral values, individuals often donate to provide public goods, because they have a desire for what is called a "warm glow" (e.g., Andreoni 1990, Ferguson et al. 2012). The term "warm glow" refers to the need to perform prosocial acts (e.g., helping others) and the simultaneous expectation to feel good afterward (Null 2011, Luccasen and Grossman 2017). Perceived moral obligations and the warm-glow effect might thus foster individuals' willingness to donate their data and to waive their right to privacy to promote social welfare.

Data donation behavior has been studied first and foremost empirically in three contexts: data donation in academia, medical data donation, and data disclosure for terror and disaster control. Regarding data donation in academia, scholars have studied the donation of data from nonresearchers to academia (e.g., Liu et al. 2017) and the sharing of data sets between researchers (e.g., Fecher et al. 2015). The donation of data from nonresearchers to academia is associated with individual costs, such as effort and loss of control, while the benefits are favorable to the public in general, for example, in the form of new basic knowledge (Breeze et al. 2012, Bezuidenhout 2013). Through the sharing of data sets between researchers, new knowledge is generated by reanalyzing existing data (Woolfrey 2009). Open access to data can also provide transparency and protect against academic misconduct (Chawinga and Zinn 2019). Research investigating what drives nonresearchers to donate their data to academia shows that key determinants include the perceived need for donation (Nov et al. 2014), the perceived reputation of the organization (Liu et al. 2017), altruism (Rotman et al. 2012, Goncalves et al. 2013), and social signals and attitude (Liu et al. 2017). Studies investigating what prevents researchers from sharing their data with the wider academic community have identified factors such as a loss of control and fear of misuse (e.g., Acord and Harley 2012, Bezuidenhout 2013), time and effort (e.g., Breeze et al. 2012, Huang et al. 2013, Chawinga and Zinn 2019), and sociodemographic variables such as age, nationality, and character traits (e.g., Acord and Harley 2012, Enke et al. 2012, Fecher et al. 2015).

While medical data are particularly sensitive (Soni et al. 2020), the factors influencing data donations in a medical and health context have considerable overlap with the findings from the academic domain. Research has shown that, for example, time and effort (Rudolph and Davis 2005, Morse 2007, Wright et al. 2010), and the fear of misuse (Lopez 2010) influence the decision to donate data in the medical and health context. Moreover, research investigating the trade-off between security and privacy in the contexts of terrorist crises and disaster control shows that fear contributes significantly to people's willingness to disclose their personal data (Davis and Silver 2004, Pavone and Esposti 2012). Even if people do not benefit directly from the disclosure of their data, they are still willing to donate their data to protect the population from terrorist attacks (Reuter et al. 2016).

The Social Dilemma of Big Data. Many people disclose their data to digital service providers and risk their privacy in exchange for even small rewards (Acquisti et al. 2013). However, the data's positive impact on social welfare cannot unfold because the organizations managing these data often do not pursue social welfare goals. To generate benefits for society at large, the data could alternatively be managed by organizations that primarily strive for increasing social welfare. These organizations may include, for example, academia, the government, and the private industry. If enough people voluntarily provide these organizations with their personal data, they could operate technologies such as smart assistants and thereby help promote social welfare.

As outlined in the introduction, data donations for a public good constitute a social dilemma. Social dilemmas are "situations in which a non-cooperative course of action is (at times) tempting for each individual in that it yields superior (often short-term) outcomes for self, and if all pursue this non-cooperative course of action, all are (often in the longer-term) worse off than if all had cooperated" (Van Lange et al. 2013, p. 126. The social dilemma of big data involves not only a social conflict (individual vs. collective interests) but also a temporal conflict (short-term vs. long-term consequences). For the individual, the protection of privacy expires immediately, while for society, the positive impact of a sufficiently large database comes with a time delay (Van Lange et al. 2013). We define the social dilemma of big data as a delayed public good dilemma, which means that individuals must give their data so that, over time, a large and diverse data set emerges that various organizations can then use with the goal to increase social welfare. Individuals cooperate in public good dilemmas, for example, because they feel a moral obligation (Chen et al. 2009), because they know that their cooperation contributes positively to the public good (Kerr 1992), and because they believe that other individuals will also cooperate and contribute (Dawes et al. 1976).

Another important characteristic of the social dilemma of big data is uncertainty. When disclosing personal data for a public good, individuals face two types of uncertainty: environmental uncertainty (i.e., uncertainty about the situation and conditions for obtaining the public good) and social uncertainty (i.e., uncertainty about the decisions of others) (Orbell et al. 1988). Thus, individuals do not know the exact threshold of data required to generate a usable database that can increase social welfare. The critical data mass depends on factors such as data quality, variety, and use. Furthermore, individuals do not know whether a sufficient number of other people are also cooperating and donating their data and, thus, whether an increase in social welfare can be achieved. Both social and environmental uncertainty lead to lower cooperation rates in public good dilemmas (Wit and Wilke 1998), in some cases through a reduced perceived obligation to cooperate (Fleishman 1980).

4.1.3 Hypotheses Development

The costs and benefits of a product or service affect individual behavior. This relationship applies to charitable donations (e.g., Acord and Harley 2012, Bezuidenhout 2013) and technology usage behavior (Dinev and Hart 2006) as well. Privacy costs are central in the disclosure of personal data. If an individual's privacy is violated, he or she may face severe negative long-term consequences. For example, the leakage of financial, health, or location data can serve as a diagnostic measure of sensitive individual attributes, such as religious or political views and possible health concerns (Gambs et al. 2011). Consequently, and as we argued previously, the sharing of personal data for a public good structurally resembles a social dilemma.

In developing our hypotheses, we rely on the literature that investigates cooperative behavior in self-sacrificing dilemmas under risk and social uncertainty. What influences individual decision making in a social dilemma is its payoff structure (e.g., Rapoport 1967, Komorita and Parks 1994). It is well documented that negative payoffs such as personal costs lead to significantly lower cooperation rates in social dilemmas (e.g., Dawes 1980, Cress et al. 2006, Gangadharan and Nemes 2009). Thus, we hypothesize the following:

> ***Hypothesis 1a:*** *A lower privacy risk increases the WDPD to a database that can be used to promote social welfare.*

The *WDPD* varies with the nature of the generated benefit (e.g., Sun et al. 2015, Dienlin and Metzger 2016). Benefits can be symbolic, hedonic (e.g., additional values such as better service or offer personalization), and utilitarian (e.g., goods, monetary advantages) (Xu et al. 2009, Sun et al. 2015). Individuals weigh their own privacy costs against the enhancement of social welfare using a cost-effectiveness analysis, a subcategory of a cost–benefit analysis (Newcomer et al. 2015). The perceived effectiveness of donations or social behavior increases the willingness to actually donate or perform social behavior. The greater the positive outcome of a donation, the greater is the willingness to donate (Ye et al. 2015).

The same is true for certain contexts of data donation. For example, people are more willing to release their data for terrorism protection if they believe the data will have an impact (Reuter et al. 2016). In social dilemmas, the positive outcome of individual cooperation is expressed in payoffs. Uncertainty in payoffs typically reduces the willingness to cooperate (Budescu et al. 1990, Levati and Morone 2013), for example, by providing a justification for noncooperative behavior (Van Dijk et al. 2004). Moreover, individuals are more willing to incur personal costs and contribute to a public good the higher the payoff levels, even if they are uncertain (Dawes 1980, Dickinson 1998, Balliet et al. 2011). Efficacy plays a major role in cooperative behavior as well (Kerr 1992). The greater the impact an individual can have through a cooperative action such as data disclosure, the more willing he or she is to incur personal costs such as privacy risk. We therefore hypothesize that the more willing individuals are to donate their personal data to promote a database as a public good, the greater is the positive impact of the database on social welfare.

> ***Hypothesis 1b:*** *A greater positive impact of the database-driven smart assistant on social welfare increases the WDPD.*

In a social dilemma with privacy risk as a personal cost, no direct personal payoffs, and uncertain and delayed societal payoffs, it may not be rational for individuals to donate their data based on a cost–benefit analysis. However, individuals might do so anyway, because they perceive data donation as the morally appropriate action. Decisions are not always an outcome of a cost–benefit analysis, but of personal beliefs about what is right and wrong. The importance of normative concerns in the context of social dilemmas is emphasized in popular models, such as the appropriateness framework of Weber et al. (2004). The appropriateness framework posits that cooperation decisions are essentially influenced by three factors that make individuals ask themselves, "what should a person like me do in a situation like this?" One of the three factors is the use of decision rules and heuristics (e.g., treating others as one would like to be treated). Morality plays a central role in general prosocial and environmental behavior (Van Liere and Dunlap 1978), in charitable-giving behavior (Sanghera 2016), and cooperative behavior in public good dilemmas (Chen et al. 2009). People often judge the morality or the moral obligation of certain decisions based on utilitarian criteria (Kahane et al. 2015). According to classical utilitarianism, decisions should be made according to the criterion of maximizing social welfare, regardless of what would be best for oneself or loved ones (Bentham 1789, Sidgwick

1907). Moral judgments play a critical role in motivating and enforcing human cooperation in social dilemmas (Gray et al. 2012). One of the underlying mechanisms is that people experience positive emotions after behaving according to their perceived moral obligations (Andreoni 1990) and negative emotions such as guilt or remorse when ignoring perceived moral obligations (Rivis et al. 2009). We therefore expect individuals to be more likely to donate their data if they perceive data donation as morally obligatory based on their internal norms.

> ***Hypothesis 2a:*** *The perceived moral obligation to donate data to a database is associated with a greater WDPD.*

Emotion-based moral judgments are based on intuitions and feelings and are often formed quickly and intuitively (Greene et al. 2001, Wheatley and Haidt 2005, Haidt 2007). Moral reasoning follows *ex post*. Emotion-based moral evaluation has historical connections with the view of Hume (1751) and Smith (1759) (see also Cubitt et al. 2011). In quick and intuitive gut reactions, moral evaluations may differ even in nearly identical scenarios: moral evaluations are situation-specific and dependent on framing (e.g., Krebs 2008). Judging with utilitarian criteria, the greater the positive impact on social welfare from an action, the greater is the perceived moral obligation to perform this action. We thus argue that donating data could be perceived as morally more obligatory the greater the impact of the database-driven smart assistant on social welfare. The impact of the smart assistant on social welfare may thus support the decision to donate data *because* of an increased perceived moral obligation to do so. Moral judgments can also be self-serving if people evaluate actions differently when the consequences affect them personally and their loved ones than when a third group is affected (Greene 2014). Thus, when a prosocial action implies negative consequences for the individual, such as the risk of a data leak, he or she subconsciously tends to evaluate an action as less morally obligatory. In this way, individuals intuitively reduce cognitive dissonance and negative emotions, if a prosocial action is not actually undertaken. We argue that donating data could thus be perceived as less morally obligatory the higher the privacy risk the individual thereby incurs.

Hypothesis 2b: *The perceived moral obligation to donate data mediates the effects of the privacy risk and the impact of the smart assistant on the WDPD.*

If a person chooses to donate his or her personal data to support a public good such as a database, he or she will subsequently have no insight into whether the data will actually be used for the declared purpose, such as to increase social welfare. Given this uncertainty, the reputation of the data-collecting organization is an important factor when making the donation decision. Bednall and Bove (2011) find that a positive reputation of the collecting organization motivated people to donate more blood. The more positive the organization's reputation, the greater are the perceived integrity and trustworthiness and the lower is the perceived risk associated with the donation. Comparable effects are also observed for other donation behavior. A charity's reputation has a significant influence on whether a donation is taken into consideration (Bendapudi et al. 1996). Drawing on these findings, Liu et al. (2017) examined the interplay between the reputation of the collecting organization and the willingness to provide data to academia. The results highlight the relevance of reputation in the context of data donation: A positive reputation promotes a willingness to provide data.

This relationship is driven by a reduced fear of privacy violation, a more credible need to donate, and a more positive attitude toward data donation in general. The reputation of an organization influences the trust people have in it. Trust is an important driver of cooperative behavior (Bednall and Bove 2011, Balliet and Van Lange 2013) and is especially relevant in cooperation decisions under uncertainty (Yamagishi 2011), which characterize data donation decisions with privacy risks and uncertain outcomes. We therefore assume that individuals ascribe different attributes to organizations that collect data to build a database to increase social welfare and, accordingly, vary in their willingness to disclose data to them. We expect the willingness to provide data to academic and governmental organizations to be greater than that to the private industry, because the private industry primarily pursues profit-maximizing interests (Bhattacharjee et al. 2017, Eyster et al. 2020) and are trusted less to promote social welfare (Lin-Hi et al. 2015).

> ***Hypothesis 3:*** *The WDPD is different for a database operated by academia, the government, and the private industry to develop and run a smart assistant.*

Computers and algorithms become increasing important components of decision-making processes (Esmaeilzadeh et al. 2015, Inthorn et al. 2015). Although individuals consistently rely on technological support to make decisions, they tend to rely less on algorithm-generated information than on human-generated information (Önkal et al. 2009). People tend to have an algorithm aversion (Dietvorst et al. 2015). This aversion is particularly pronounced when people have seen an algorithm generate erroneous information; even if the algorithm is known to provide better decision support on average than a human (Dietvorst et al. 2015), people are more intolerant of small errors made by algorithms than of large errors made by humans (Dietvorst et al. 2015). The technical nature of algorithms is increasingly characterized not only by automation but also by autonomy. De Visser et al. (2018, p. 1409) define autonomy as “technology designed to carry out a user’s goals, but that does not require supervision.” Smart assistants are based on autonomous algorithms as well. When investigating data donation choices, it is therefore important to consider that the technical nature of a smart assistant determines how the data are analyzed to derive personalized information (e.g., specific tips and action recommendations).

We assume that, in simplified terms, two types of algorithms vary in their autonomy degrees. In case of a smart assistant with a *self-learning algorithm*, rules for personalization autonomously change depending on how the user reacted to past information. Consequently, the selected personalized recommendation will also change over time, depending on the rules the smart assistant automatically modified. In case of a smart assistant with a *human-supervised algorithm*, rules for personalization do not autonomously change depending on how the user reacted to past information; however, a human can manually change the rules. Consequently, the selected personalized recommendations will change over time, depending on the rules a human manually modified. We hypothesize that because of algorithm aversion, individuals would prefer a smart assistant whose decision support is not fully automated but can, to some degree, be modified by a human. Research on how to overcome algorithm aversion shows that people do not prefer complete autonomy and are significantly more likely to use even imperfect algorithms if they can easily modify the algorithm (Dietvorst et al. 2018).

A data-driven technology's service such as a smart assistant's decision support for a large group of people or entire societies could not or only with disproportionate effort be entirely provided by humans. Despite this, the autonomy of the smart assistant could, however, be designed to varying degrees, as in the case of a human-supervised and self-learning smart assistant. Drawing from the literature on algorithm aversion, we therefore hypothesize that individuals would be more likely to donate their data to a database if the data were used to operate a smart assistant with reduced autonomy.

> ***Hypothesis 4:*** *The WDPD is greater for a database that is used to develop a human-supervised smart assistant than for a database that is used to develop a self-learning smart assistant.*

4.1.4 Empirical Implementation

Experimental Design and Interventions. We conduct an online experiment with treatments that rely on between-subjects and within- subject designs to test our hypotheses. The experiment has a 3 × 3 design and is followed by an online survey to control for potential confounding variables and characteristics. The experiment considers two domains, both of which include the identical 3 × 3 design but vary in the social welfare domain promoted by the smart assistant: a sustainable environment (domain 1) and a sustainable health system (domain 2). The experiment has been preregistered at the AEA RCT Registry and obtained ethical approval from the Ethics Commission of the authors' university.

Before participating in the experiment, individuals received an explanation that the UN has launched a call for more data to support the Social Development Goals and how public goods benefit from that data. Participants learned what a smart assistant is, how it can use data to promote the goals, and why it needs a sufficient amount of data to do so. Participants were further advised that the disclosure of data always involves certain privacy risk. We then provided the participants with the following scenario (domain 1): "A smart assistant could support US users in living environmentally friendlier everyday lives, thereby promoting a sustainable environment. Every

English-speaking person with a smartphone in the United States could use the smart assistant. However, to develop and operate an assistant that offers informed and comprehensive decision support on environmentally friendlier behavior, there must be access to a sufficiently large database of diverse and trustworthy data. The database requires a given list of data sets in an anonymized form." We asked participants to imagine that they could easily and anonymously upload their personal data to the database. We presented participants with two options. Either they could donate their data to the database, accept a certain level of privacy risk, and contribute to the development of a smart assistant that has an impact on a sustainable environment or they could not donate their data, completely avoid the associated privacy risk, and not contribute to the development of a smart assistant that has an impact on a sustainable environment.

The actual experiment consisted of three parts. In part 1, we provided participants with one of three varying levels of risk of their data getting leaked (treatment 1) combined with one of three varying levels of the impact of the smart assistant on social welfare (treatment 2). We randomly assigned the participants to the domains and nine treatment combinations through a designated function of the software Unipark. Figure 4 depicts an overview of the treatments per domain.

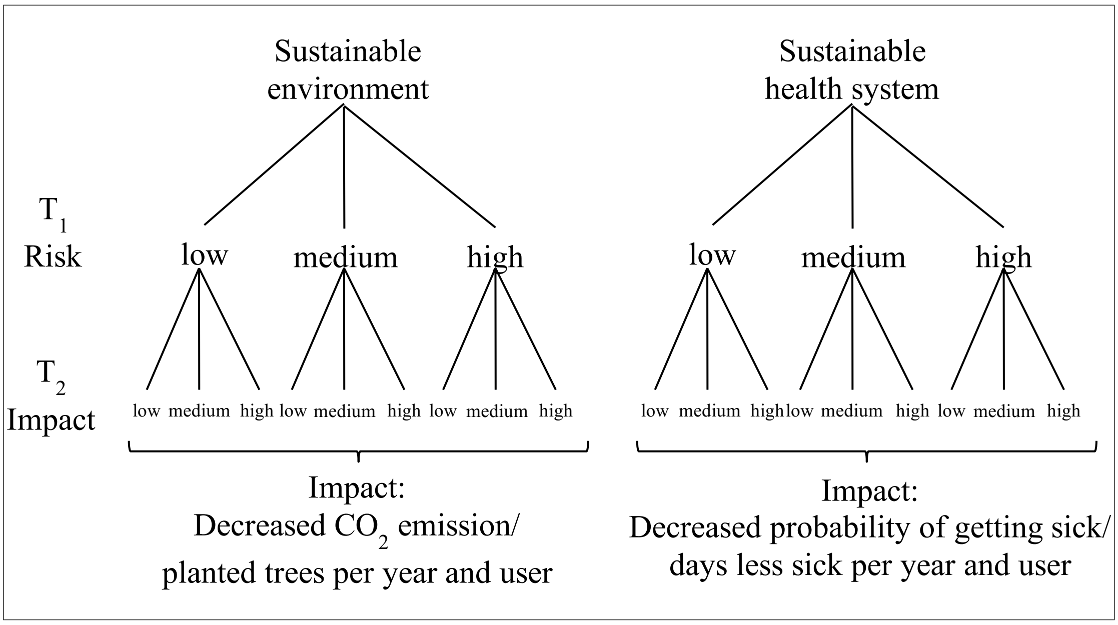


Figure 3. Experimental interventions.

The operationalization of the risk treatment was identically for both domains using the following wording: "The risk of data being leaked from this type of database is approx. [0.001/10/20]%. This corresponds to the leakage of data from [1 of 1,000/10 of 100/20 of 100] individuals." Because no reliable academic quantification of data leak probabilities exists, we consider the risk interval between 0.001% and 20% realistic, in line with a recent report of a large cybersecurity company (Varonis 2019). We also calibrated the chosen risk levels in a pretest with 195 students from the faculty of business studies and economics at the authors' university. In the online experiment, we showed all participants a list of data types they would provide if they donated, because the willingness to provide data clearly depends on the categories of data to be provided (Phelps et al. 2000). The shown list of data categories came from the Personal Information Protection Commission (2013) (see also Lim et al. 2018).

The operationalization of the impact treatment was different for each domain. In domain 1, the smart assistant supported its US users in living environmentally friendlier everyday lives, thereby promoting a sustainable environment. We operationalized the impact treatment using the following wording (domain 1): "By giving informed and relevant decision support, the smart assistant decreases the yearly CO_2 emissions of each user by approx. [50/30/10]%. This corresponds to planting [440/264/88] trees per year per user." To consider realistic impact levels of the smart assistant, the environmental impact is an approximate calculation of a person's CO_2 savings potential based on statistics from the German Federal Environment Agency (2020). To give participants a more intuitive measure of the avoidable CO_2 emissions, we reported the equivalent number of trees that would be required to compensate for the respective CO_2 emissions. The calculations are based on statistics from Klein (2009). In domain 2, the smart assistant supported its US users in living healthier everyday lives, thereby promoting a sustainable US health system. We operationalized the impact treatment using the following wording: "By giving informed and relevant decision support, the smart assistant decreases the probability of getting sick by approx. [50/30/10]%. This corresponds to a [five-/three-/one-] day decrease per year in the user getting sick." To consider realistic impact levels of the smart assistant, we calculated the impact on the health system according to a person's potential for health improvement, in line with Nieman et al. (2011), who reports a negative relationship between regular physical activity and upper respiratory tract infections. To illustrate the potential impact of health improvements to the participants, we reported the equivalent number of days a person would be sick less per year. The calculation is based on statistics from the Harvard School of Public Health (2016) and Molinari et al. (2007).

All participants took part in part 1 of the experiment (see Figure 4 for an overview). Then, they were randomly assigned to either part 2a or part 2b of the experiment. In part 2a and 2b, participants could choose between different databases when donating their personal data. All databases required the same data, had an identical privacy risk, and were used to develop a smart assistant that promotes one of the two social welfare domains. The risk and impact levels corresponded to the treatment combination assigned in part 1. The databases in part 2a differed in terms of the organization that operates the respective database to develop and run a smart assistant: academia was operationalized by an Ivy League university, the government was operationalized by a federal US agency, and a profit-oriented organization was operationalized by a large US tech company. The databases in part 2b differed in terms of the technical nature of the smart assistant, which would be developed depending on the respective database: a smart assistant using a self-learning algorithm and a smart assistant using a human-supervised algorithm to derive personalized information (e.g., specific tips and action recommendations) to promote environmentally friendlier or more healthful user behavior. We did not operationalize the individual algorithm type further but briefly explained it to participants (see Appendix A2.5).

Target Population and Sample. We test our hypotheses on US citizens. Participants were recruited from the crowdworking platform MTurk. Although a sample from MTurk is not necessarily representative of the US population, various studies have successfully replicated a wide range of established economic and psychological effects and empirically validated the use of MTurk as a useful data collection tool (Schnoebelen and Kuperman 2010, Gibson et al. 2011, Becker et al. 2012, Crump et al. 2013), and relevant research that relies on MTurk respondents has achieved robust results (Bonnefon et al. 2016). Furthermore, MTurk samples are considerably more heterogeneous than student samples from laboratory studies (Hussy et al. 2010). Crowdworkers on MTurk have a particularly diverse backgrounds (Mason and Suri

2012), which are crucial for the external validity of our results. We targeted the online study exclusively at workers who are US citizens and over 18 years of age.[14]

We executed the experiment by posting a human intelligence task (HIT) on MTurk. The HIT provided a description of the task, the participation requirements, compensation, and instructions on how to proceed. Interested MTurk workers were instructed to click on a survey link, which forwarded them to an online survey in Unipark. Participants received between US$0.40 and US$0.55 for taking part in the HIT, depending on how they answered incentivized items on the expected donation behavior of others and their social value orientation in the survey. On the last page of the survey, the workers received an automatically generated unique code that they had to enter back on the MTurk website to trigger their payment. Workers could only participate once in the HIT.

We collected the data over a two-day period (September 14 and 15, 2020). Of the 2,552 workers who clicked on the link, 1,883 filled out the online survey completely. Responses from workers were excluded from the data set if they answered at least one comprehension question incorrectly, they stated being non-US citizens, or they reported an age of less than 18 years. The final sample includes responses from 1,696 participants with an average response time of 12 minutes. In a pretest, the average response time was 19 minutes. Because we requested participants in the pretest to carefully check all potential mistakes in our survey, we consider the shorter response time during the HIT reasonable. The participants were randomly assigned to the domains and treatments.

Variables. We consider two dependent variables. First, we investigate participants' *WDPD* depending on the risk level and impact of the smart assistant. Second, we investigate their relative *WDPD* to different managing organizations and types of algorithms. To test hypotheses 1a and 1b, participants needed to indicate their *WDPD* on a 1–100 slider. We adapted the original wording of Bonnefon et al. (2016) to the activity of data donation. The variable is the response to the following question: "How

[14] We ensured these characteristics by providing a clear description of requirements to participate in the introduction of the study on MTurk and by additional queries during the study.

inclined are you to upload your personal data to the database?" (0% = not at all likely; 100% = extremely likely).

To test hypotheses 2a and 2b, we measure the moral obligation to provide data. Participants indicated their moral obligation on a 5-point Likert scale. We adapted the original wording of Kahane et al. (2015) to the activity of data donation. The variable is the mean response to the following two questions: "Do you think that there is a moral obligation for people to upload their personal data to the database?" (1 = It would be wrong for people to upload their personal data to the database; 3 = People don't have to upload their personal data to the database, but it would be nice if they did; 5 = People must upload their personal data to the database) and "How morally wrong is it if people do not upload their personal data to the database?" (1 = perfectly fine; 3 = neither fine nor wrong; 5 = deeply wrong).

To test hypothesis 3, we investigate the relative *WDPD* to each of the presented operating organizations of the database (academic, governmental, and profit-oriented organizations). *WDPD* and relative *WDPD* rely on the same question; however, the question items differ in their respective answering options (Bonnefon et al. 2016). For *WDPD*, participants responded using a single slider. To identify the relative *WDPD* variable, participants needed to use multiple sliders in relation to each other, with the sum of the sliders equaling 100. Thus, indicating their individual willingness to provide data to one of the databases negatively correlated with their willingness to provide data to the alternative database. We used related sliders because we are primarily interested in ranking the *WDPD* per operating organization rather than the absolute magnitude of *WDPD* per operating organization. Survey items that use fixed total budget partitioning are particularly suitable for examining rankings and differences between interdepend options (Conrad et al. 2005, Fabbris 2013). To test hypothesis 4, we investigate the relative *WDPD* to each of the databases used to develop smart assistants with different degrees of human involvement (self-learning algorithm vs. human-supervised algorithm).

In addition to the variables of interest that enable us to test our hypotheses, we consider control variables on participants' sociodemographic situation, values, and attitudes in the final part of the survey. We collected the following variables to test explanatory channels: the perceived benefit to the individual user relative to the perceived benefit to the general public from the smart assistant, perceived individual preference for a sustainable environment and health system, profit-orientation, and trustworthiness and technical skills of each operating organization as perceived by the participants. Because psychological and attitudinal characteristics can explain cooperative behavior that includes temporal conflicts and technology usage, we consider the following control variables: human-assistant trust (Madsen and Gregor 2000), interpersonal distrust (Eurobarometer 2014), future time orientation (specifically time perspective and anticipation of future consequences) (Gjesme 1979, Steinberg et al. 2009), self-reported health (Idler and Angel 1990), self-reported environmentally friendly behavior (Idler and Angel 1990), and risk attitude (Weber et al. 2002). Given their particular relevance in explaining cooperative behavior under uncertainty, we collected social value orientation (Murphy et al. 2011) and the anticipated behavior of others using monetary incentivized tasks, to encourage honest and realistic responses (see Appendix A2.7). We collected the following demographic variables: gender, age, income, political and religious orientation, education, income, living standard, and citizenship. All control variables are balanced across treatments and domains (see Appendices A and B).

Empirical Approach. To test hypotheses 1a and 1b, we use analyses of variance (ANOVAs) to determine whether we can reject the following H_0 in a between-subjects design (mean value of $WDPD = \mu$; treatments: R = risk of data getting leaked, I = impact of the smart assistant; treatment levels: l = low, m = medium, h = high):

$$H_0(risk): \mu_{Rl} = \mu_{Rm} = \mu_{Rh}.$$

$$H_0(imp): \mu_{Il} = \mu_{Im} = \mu_{Ih}.$$

The alternative hypotheses, which we test using Tukey's method, are

$$H_A(risk): \mu_{Rl} > \mu_{Rm} > \mu_{Rh}.$$

$$H_A(imp): \mu_{Il} < \mu_{Im} < \mu_{Ih}.$$

To test hypothesis 2a in a within-subject design, we use the following ordinary least squares regression:

$$(1)\ WDPD\ = \beta_0\ + \beta_1 MO + \beta_2 \mathrm{R} + \beta_3 \mathrm{I} + \beta_4 \mathbf{C} + \varepsilon,$$

where *MO* is perceived moral obligation to provide data and $\mathbf{C}$ is a vector of control variables, such as risk attitude and social value orientation. Hypothesis 2a is identified when a high *MO* is associated with a greater *WDPD*.

We expect a low risk of a data leak and a larger positive impact of the smart assistant on social welfare to have a positive and direct effect on *WDPD*. However, *MO* may mediate the effect of risk of a data leak and the impact on social welfare on *WDPD*. We therefore perform a mediation analysis to investigate the extent to which the effects of these two explanatory variables on *WDPD* pass through *MO* in our baseline specification. For mediation analysis, we need to also estimate the following two regressions.

$$(2)\ WDPD = \beta_0 + \beta_1 R + \beta_2 I + \beta_3 \mathbf{C} + \varepsilon.$$

$$(3)\ MO = \beta_0\ + \beta_1 R + \beta_2 I + \beta_3 \mathbf{C} + \varepsilon.$$

The mediation for the risk of a data leak (hypothesis 2b) is identified when four conditions are met. First, the risk of a data leak variable (*R*) has a significant effect on *WDPD* in Model 2. Second, the risk of a data leak (*R*) has a significant effect on the mediator variable *MO* in Model 3. Third, in Model 1 the mediator variable *MO* has a significant effect on *WDPD*. Fourth, the coefficient of β_1 must be smaller in absolute terms in Model 1 than in Model 2. The mediation for the smart assistant's impact on social welfare is identified analogously.

To test hypothesis 3, we examine whether we can reject the following H_0 in a between-subjects design:

$$H_0\colon \mu_{rWDPD(gov)} = \mu_{rWDPD(tech)} = \mu_{rWDPD(acad)},$$

where *rWDPD* is relative *WDPD*, *gov* is a federal US agency, *tech* is a large US tech company, and *acad* is an Ivy League university.

The alternative hypothesis is

$$H_A\colon \mu_{rWDPD(gov)} < \mu_{rWDPD(pi)} < \mu_{rWDPD(acad)}.$$

We test the specified relationships of the parameters with a common two-step multiple comparison test procedure (Kao and Green 2008). First, we perform an ANOVA to check whether there are differences between the mean values. Second, we perform a post hoc analysis using Tukey's method to test the direction of the differences between mean values. Tukey's method has the special characteristic of keeping the type I error level constantly close to 5%, thus avoiding running into a type II error too often (Chen et al. 2017).

To test hypothesis 4, we use a one-sided t-test to examine whether we can reject the following H_0 in the between-subjects design:

$$H_0: \mu_{rWDPD(SL)} \geq \mu_{rWDPD(HS)},$$

where SL is the self-learning algorithm and HS is the human-supervised algorithm.

4.1.5 Results

The Willingness and Perceived Moral Obligation to Donate Data for Public Goods. Figure 5 reports the mean willingness and the mean moral obligation to donate personal data. The average willingness to provide data to a database to promote social welfare is 54.31 (SD = 30.30) on a scale from 1 to 100 (50 = neutral score), which is significantly different from 0 ($p < .001$). Thus, participants show a significant tendency to donate their data for a public good. With an average of 55.10 (SD = 30.31), the *WDPD* in the environment domain is no greater than that in the health domain, with an average of 53.50 (SD = 30.29), as a t-test shows no significant differences (p = .139). The average perceived moral obligation to donate personal data to promote social welfare is 3.03 (SD = .935) on a scale of 1 to 5 (3 = neutral score). Thus, participants feel an above-average moral obligation to donate their data. Note that there are differences between the domains. The participants feel a slightly greater moral obligation to donate their data for a sustainable environment (μ_{MO_env}= 3.06) than for a sustainable US health system (μ_{MO_health}= 2.99), which is statistically significant at conventional levels (p = .046).

One potential reason for this difference is that the distribution of the perceived benefits to social welfare differs across domains. To account for the different characters of the two domains in explaining the results, we asked participants to indicate on a scale from

1 to 100 how much an individual smart-assistant user and the general public benefit in each domain of social welfare. We find that participants believe that individual users benefit significantly more from a smart assistant that improves their personal health status (μ_{user_health}= 47.25) than from a smart assistant that improves their carbon footprint (μ_{user_health}= 44.80; p = .004). By contrast, the public apparently benefits significantly more from a smart assistant that promotes a sustainable environment (μ_{pub_env}=54.74) than from a smart assistant that promotes a sustainable US health system (μ_{pub_health}=52.15; p=.003). The higher ascribed utility for the general public could be an explanation for a greater perceived moral obligation to donate data in the environment domain, though this greater moral obligation does not translate into a greater *WDPD*.

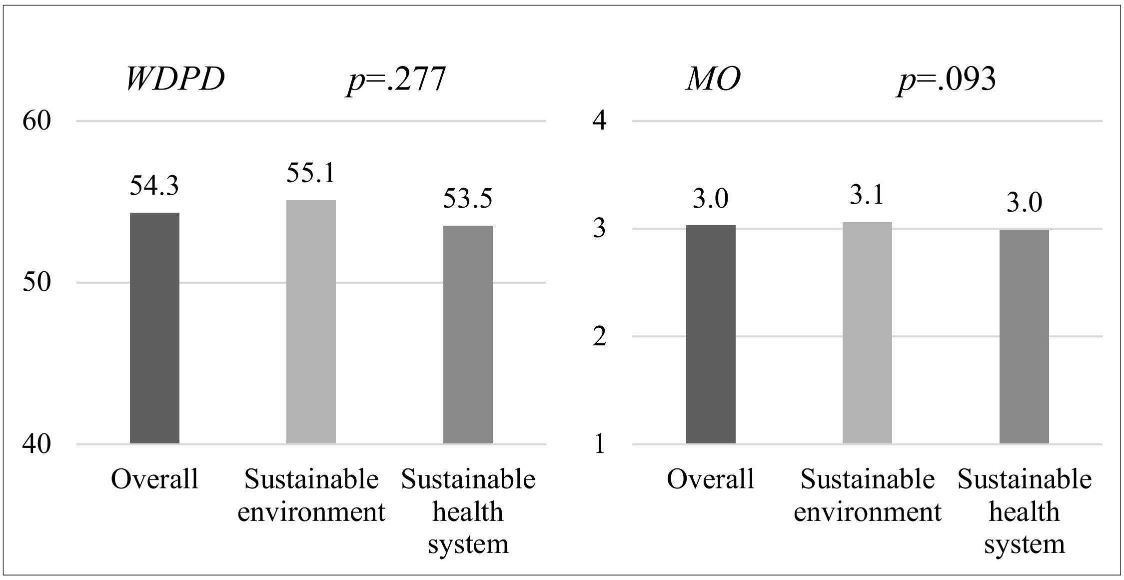


Figure 4. *WDPD* and *MO* to donate personal data. *Note*: The figure provides p-values from t-tests of mean differences across the two domains.

Effects of Risk of Data Leak and Data's Impact on Social Welfare when Donating Data. Is a low risk of a data leak and/or a high impact of the smart assistant on social welfare associated with a greater *WDPD* (H1a/H1b)? To answer this question, we compare the willingness to provide data to a database. Figure 6 summarizes the results per treatment and domain.

In the risk treatment, the ANOVA and Tukey's method results show that the *WDPD* across the three treatment conditions varies significantly depending on the level of risk (p = .007). The higher the risk that the data is leaked, the lesser is the *WDPD*. The willingness differs between a low risk level (μ_{WPD_Rl}=57.60) and higher risk levels (medium: μ_{WPD_Rm}= 52.43, p = .012; high: μ_{WPD_Rh}= 52.91, p = .024). However, whether the risk of a data leak is medium or higher is irrelevant for individuals' *WDPD*, as the Tukey's method results show no significance differences in the *WDPD* (p = .960) under medium (10%) or high (20%) risk levels. The insensitivity to higher risk levels is striking given that the percentage-point difference between the medium (10%) and high (20%) risk levels is nearly identical to the percentage-point difference between the low (0.001%) and medium (10%) risk levels. It seems that individuals consider the difference between 0.001% and higher risk levels binary (i.e., a 0.001% risk is considered "no" risk of a data leak, while a 10% and 20% risk are considered "some" risk of a data leak). While the *WDPD* differs between low and medium risk levels in the environmental domain (p = .033), we find no such differences in the US health system domain (p = .133). Overall, hypothesis 1a receives support in the sustainable environment domain but not in the US health system domain.

In the impact treatment, the ANOVA and Tukey's method results show that *WDPD* does not differ for the varying treatment levels of the smart assistant's impact on social welfare, neither overall (p = .808) nor in either of the two domains (environment: p = .442; US health system: p = .438). The extent of the positive impact of the database-driven smart assistant on a sustainable environment or US health system appears largely irrelevant to the decision to donate data for realistic impact levels. Thus, we find no support for hypothesis 1b.

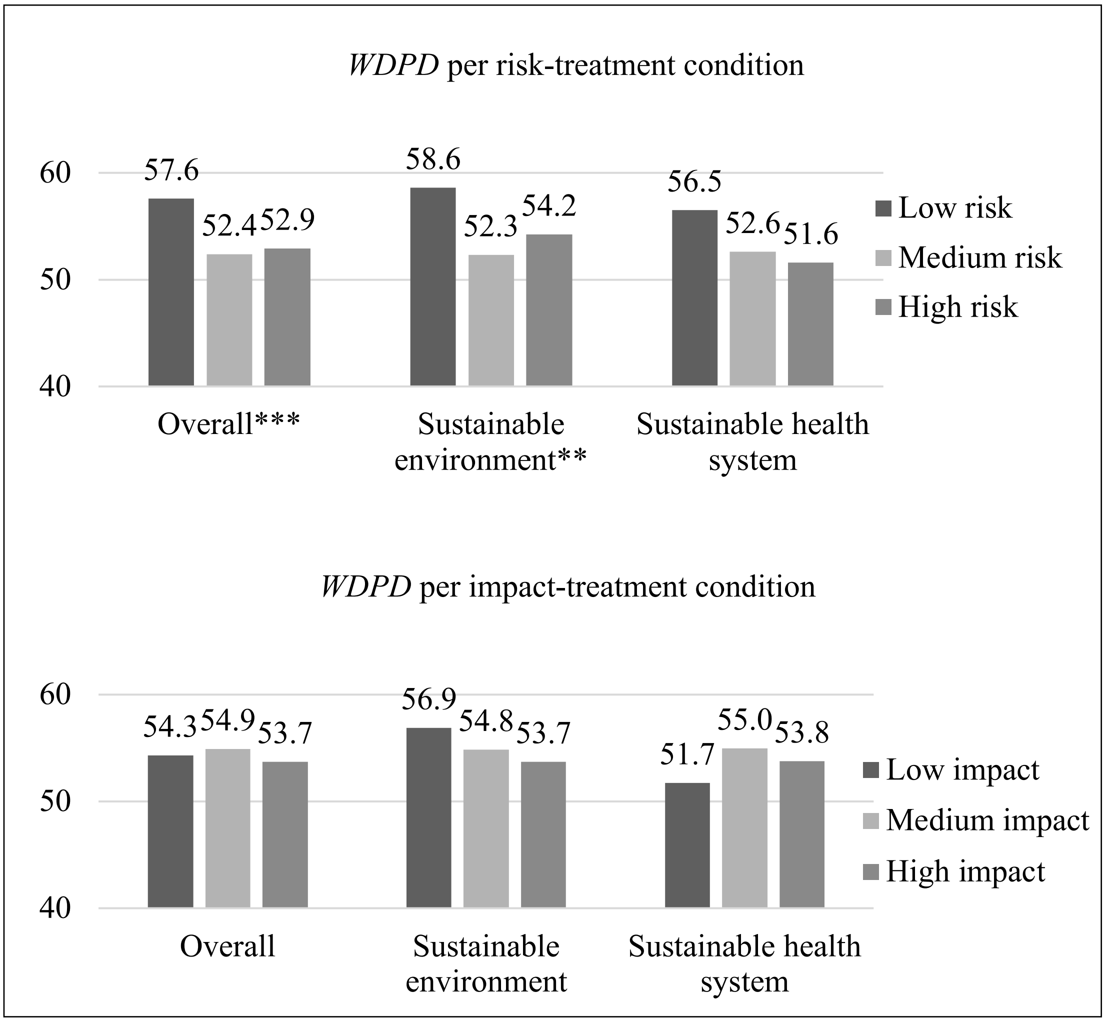


Figure 5. *WDPD* per treatment and domain. *Note*: Tukey's method results on the pairwise group comparisons of the *WDPD* per treatment condition are reported in Appendix A, Table A.1.8 . † $p < .1$; ** $p < .05$; *** $p < .01$.

Effect of perceived moral obligation when donating data. Is a high perceived moral obligation to donate personal data associated with a greater *WDPD* (H2a)? If so, does the perceived moral obligation mediate the effect of risk or impact on the WDPD (H2b), or does it have a direct effect only? To answer these questions, we run three regressions.

Table 4 shows the regression results of Model 1 for the overall sample and the sustainable environment or US health system domain. The results show that a greater moral obligation to donate personal data is significantly associated with a greater *WDPD* ($p < .001$). An increase of the *MO* of one scale point increases the *WDPD* by 12%. The impact of *MO* on *WDPD* also holds when differentiating between the two domains of social welfare (sustainable environment: $\beta = 10.219$; $p < .001$; sustainable US health system: $\beta = 9.693$; $p < .001$). Thus, hypothesis 2a is supported and cannot be empirically rejected. The control variables with a positive and significant effect on *WDPD* are living standard ($\beta = 1.964$; $p = .014$), education ($\beta = 1.484$; $p = .005$), human-assistant trust ($\beta = 10.585$; $p < .001$), interpersonal distrust ($\beta = 1.515$; $p = .038$), and the anticipated data donation behavior of others ($\beta = .218$; $p < .001$); only age ($\beta = -.030$; $p = .001$) has a negative and significant effect on *WDPD.* Model 1 further supports the previous results regarding the relevance of risk ($p < .001$) and shows no significant effect for the smart assistant's impact levels on *WDPD*.

Table 5 gives on overview of the mediation analysis results from regression Models 2 and 3. Overall and in both domains, three of the four mediation conditions are met in the risk treatment. Only the significance of the negative effect of risk on the perceived moral obligation is not statistically significant at conventional levels (overall: $\beta = .032$; $p = .112$). In the impact treatment, the mediations conditions 2 and 4 are mainly not met. A differentiation between the domains also shows that, though the results suggest that moral obligation mediates the effect of risk on the *WDPD*, there is no empirical support for hypothesis 2b.

Table 4. *WDPD*

Domain	*DV: WDPD (OLS regressions)*		
	Overall	Sustainable environment	Sustainable health system
Moral obligation	**11.788***** (.786)	**10.220***** (1.133)	**9.694***** (1.111)
Risk	**-3.057***** (.622)	**-3.076***** (.852)	**-7.509***** (1.747)
Impact	-.370 (.620)	**-1.607**† (.851)	.625 (1.749)
Age	**-.030**** (.009)	-.043 (.052)	**-.027***** (.009)
Education	**1.484***** (.529)	**1.626**** (.707)	.323 (.741)
Female	.130 (1.065)	.635 (1.444)	.418 (1.479)
Income	.136 (.277)	.067 (.379)	.406 (.383)
Living standard	**1.964**** (.799)	1.722 (1.082)	1.643 (1.80)
Political views	.904 (.678)	.023 (.902)	-.431 (.932)
Religious views	-.640 (.581)	-1.270 (.801)	-1.95 (.760)
Expected behavior others	**.218***** (.028)	**.137***** (.036)	**.198***** (.039)
Future time orientation	-.666 (.760)	.572 (1.005)	-1.075 (1.075)
Human-assistant trust	**10.585***** (1.124)	**6.770***** (1.547)	**6.569***** (1.641)
Interpersonal trust	**1.515**** (.731)	.999 (1.092)	1.688† (.943)
Risk attitude	.510 (.963)	.174 (1.307)	-.091 (1.260)
Social value orientation	3.838 (2.609)	4.790 (3.451)	-.308 (3.562)
Benefits for the public	.012 (.088)	.054 (.114)	-.043 (.092)
Benefits for each user	.014 (.089)	.075 (.115)	-.080 (.094)
Pref. database for environment		**6.477***** (1.020)	
Pref. sustainable environment		**2.802***** (.925)	
Previous environmental behavior		-.263 (.998)	
Pref. database for health			**7.335***** (1.084)
Pref. sustainable health system			**-.174**† (.922)
Previous health behavior			1.873 (1.039)
Constant	**-40.939***** (9.701)	**-62.576***** (12.94)	**-4.981***** (10.952)

Note: The dependent variable is *WDPD*. Results are reported overall and per domain. Robust standard errors are reported in parentheses. OLS = ordinary least squares. † $p < .1$; ** $p < .05$; *** $p < .01$.

Table 5. Summary of Mediation Analyses Results per Treatment and Domain

Mediation conditions	Overall		Sustainable environment		Sustainable health system	
	risk	**imp.**	**risk**	**imp.**	**risk**	**imp.**
1. Sig. effect of *R* / *I* on *WDPD* in Model 2	✓	X	✓	✓	✓	X
2. Sig. effect of *R* / *I* on *MO* in Model 3	X	X	X	X	✓	X
3. Sig. effect of *MO* on *WDPD* in Model 1	✓	✓	✓	✓	✓	✓
4. Coefficient of β_1 is smaller in Model 1 than in Model 2	✓	X	✓	X	X	X
Total conditions met	**3 / 4**	**1 / 4**	**3 / 4**	**2 / 4**	**3 / 4**	**1 / 4**

How the Operating Organization of the Database Matters when Donating Data. Is the *WDPD* different for a database operated by academia, the government, or the private industry? Figure 7 reports the mean *relative WDPD* per domain and operating organization. The ANOVA results show that the *WDPD* varies significantly depending on which organization manages and operates the database to develop a smart assistant (p < .001). The *WDPD* is significantly lesser when the database is operated by the private industry (μ_{pr}=29.54) than by academia (μ_{ac}= 33.09; p = .001) or the government (μ_{gov}= 33.76; p < .001). However, individuals are statistically indifferent when the database is operated by academia or the government (p = .787). The results per domain are mostly similar. In both domains, the operating organization of the database is critical for the *WDPD*. In the environment domain as well, the *WDPD* is significantly lesser if the database is managed by the private industry (μ_{pr_env}= 28.45) than by academia (μ_{ac_env}= 32.41; p = .013) or the government (μ_{gov_env}= 34.61; p < .001), and individuals are statistically indifferent when the database is operated by academia or the government (p = .248). In the health domain, the average *WDPD* values show a similar tendency in absolute terms; however, the Tukey's method results only show a statistically significant difference in whether the database is managed by academia (μ_{ac_health}= 33.84) rather than the private industry (μ_{pr_health}= 30.70; p = .080).

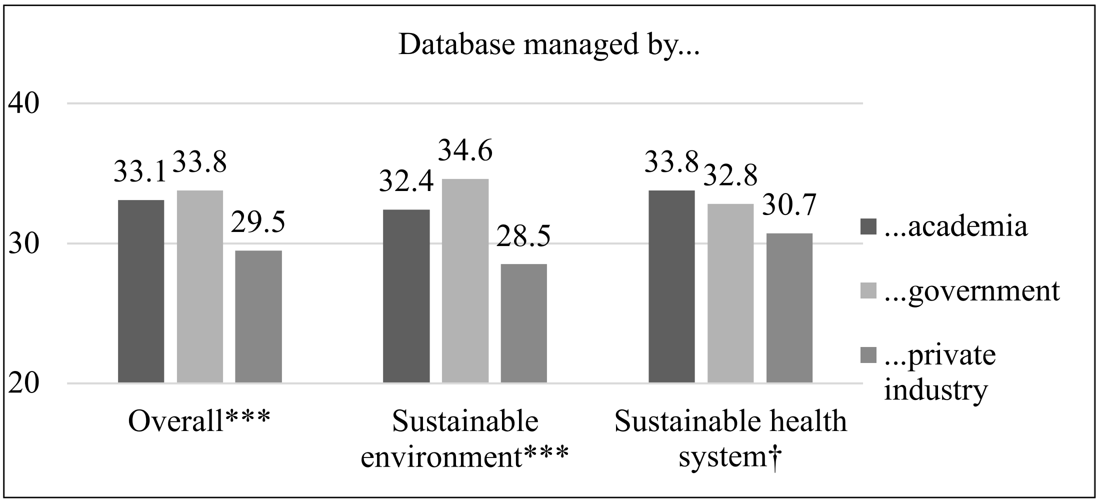


Figure 6. *WDPD* per operating organization. *Note*: Tukey's method results on the pairwise group comparisons of the *WDPD* per treatment condition are reported in Appendix A, Table A.1.9. † $p < .1$; ** $p < .05$; *** $p < .01$.

Our data provide a potential reason for the significantly lesser *WDPD* in case of an operation by the private industry. The control questions asked participants to indicate how skilled they believe each operating organization is to develop a smart assistant and how trustworthy and profit oriented each organization is. The results of an ANOVA show that participants perceive the private industry as more skilled in the development of a smart assistant than academia (p < .001) or the government (p < .001), but also as significantly less trustworthy (academia: p < .001; government: p = .002) and more profit oriented (academia and government: p < .001). A regression analysis on the *WDPD* to the private industry verifies that high trustworthiness and low-profit orientation are significantly associated with a greater *relative WDPD*, but skill in developing a smart assistant is not (see Appendix A, Table A1.12). An analogous comparison of the *relative WDPD* to academia and government also contributes to the explanation of the results. Participants perceive academia as slightly more trustworthy and skilled than the government. However, the absolute differences are marginal, and there is no statistical difference in their profit orientation.

In summary, while there is no significant difference in the *WDPD* depending on whether the database is operated by academia or the government, operation by private industry is associated with a lesser *WDPD* overall and in each domain. Overall, we find support for hypothesis 3, which cannot not be empirically rejected.

How the Type of Algorithm Matters when Donating Data. Is the *WDPD* greater for a database that is used to develop a human-supervised smart assistant than for a database that is used to develop a self-learning smart assistant? To answer this question, we compare the willingness to provide data to each database using a one-sided t-test. The results show that the algorithm type does not affect the *WDPD* either overall (p = .553) or in the health domain (p = .553). In the environment domain, the results show a tendency for participants to prefer a self-learning over a human-supervised smart assistant (p = .080). Overall, we find no empirical support for hypothesis 4. The type of algorithm is not decisive for the *WDPD*.

Robustness checks. To understand how a database can increase social welfare and the role of data-driven technologies such as smart assistants, it is important that participants carefully read the introduction of the HIT. As a robustness test, we therefore conducted all analyses reported in this article for a restricted sample that excludes participants who spent less than half of the average time to participate. Given that it took participants an average of 12 minutes to finish our HIT, in the restricted sample we deleted 360 observations with a participation time of less than 6 minutes.

The ANOVA and Tukey's method results to identify hypotheses 1a and 1b are identical for the restricted sample but show stronger significance levels for the findings that were previously significant. In the restricted sample, the risk level of a data leak still affects the *WDPD*, while the smart assistant's level of impact does not. In the unrestricted sample, we found that the risk level is only decisive for the *WDPD* overall and in the environment domain. In the restricted sample, the risk level also affects the *WDPD* in the health domain. The Tukey's method results in the restricted sample are identical to the findings overall and in the environment domain. Participants respond to an increase in risk level from low to medium and from low to high risk, but they show no sensitivity to changes from medium to high risk levels. In the restricted sample, this finding also holds for the health domain. The regression analyses, mediation analysis, ANOVAs, and t-test to identify hypotheses 2 to 4 show identical results in the restricted sample but, in general, show somewhat stronger levels of significance if treatment effects were previously significant.

We further test whether participants perceived realistic risk and impact levels differently, given the established measures we have used (Bonnefon et al. 2016). We therefore asked participants to assess the likelihood that their personal data would be leaked from the database and to assess the smart assistant's impact on a sustainable environment or health system. We used the following items on a 5-point Likert scale: "Assess the likelihood that your personal data will be leaked from the database" (1 = extremely unlikely; 5 = extremely likely) for the risk treatment, and "Assess the impact of the smart assistant on a sustainable environment [health system]" (1 = no impact; 5 = major impact) for the impact treatment. We ran ANOVAs followed by Tukey's method to check whether participants actually perceive the risk and impact levels to be different across treatment conditions (see Appendix A1.3 for details).

The results are identical to those of the ANOVAs used to identify hypotheses 1a and 1b. When testing whether participants perceived realistic risk and impact levels differently, we find that they perceive the risk differently in case of a low risk level as compared with a medium risk level and high risk level. However, participants do not perceive a medium and high risk level to be different from each another, which indicates that participants indeed consider the difference between 0.001% and higher risk levels as binary. Participants, however, do not perceive the smart assistant's impact levels to be different. This finding is in line with the notion that the benefits of a smart assistant are attributed to society at large, and the individual share might be considered too small in large groups to make contributions worthwhile (Olson 1965). In a broad sense, it is also consistent with a recent experimental result by Heeb et al. (2021), who evidence that investors put emphasis on whether an investment has a sustainable impact, but not how high the impact level actually is. The perceived indifference between impact levels is also a potential reason for the results of the main analysis, according to which the impact is not decisive for the individual willingness to disclose data to promote social welfare. We chose all impact levels on the basis of realistic assumptions and in line with real-world conditions. Although we could have selected more strongly varying impact levels and calibrated them in a pretest, insights of potential effects would be questionable because of the impact levels' detachment from reality and participant deception.

4.1.6 Discussion and Conclusion

We provide empirical evidence that individuals would donate their data to a database to promote social welfare, even if their data is at risk of getting leaked. The evidence of our online experiment further shows that the risk level of a data leak is decisive for the *WDPD* but that varying levels of impact that data realistically can have on social welfare are not. A potential explanation for this finding is that for the individual, the consequences of a data leak are direct and privacy protection expires immediately in case of a data leak, while the positive impact of a sufficiently large database arises with a time delay, and the individual only benefits to a small degree from its contribution (Van Lange et al. 2013). We find the risk of a data leak is important for databases that are used to promote a sustainable environment but not for a sustainable health system. Moreover, the stronger an individual's perceived moral obligation to donate data, the greater is his or her *WDPD*. Furthermore, individuals are less willing to provide their data to profit-oriented organizations than to academia or the government. In contrast with the algorithm aversion literature (Önkal et al. 2009), individuals are not sensitive to whether the data is processed by a human-supervised or self-learning smart assistant.

Our online experiment is not without limitations. First, our findings rely on a sample of US citizens. A sample of participants from other countries and cultures might yield different results. For example, cultural influences are crucial for individuals' self-disclosure on social media sites (Krasnova et al. 2012) and for general risk perception (Weber and Hsee 1998). We further anticipate that *WDPD* will be greater in collectivist societies than in individualist societies due to greater social value orientation (Shahrier et al. 2016) and willingness to cooperate in social dilemmas (Probst et al. 1999).

Second, we conducted our experiment using a hypothetical choice scenario. On the one hand, we expect the self-reported *WDPD* to be greater than the actual data donation behavior because information privacy research shows an intention–behavior gap in self-disclosure (e.g., Joinson et al. 2010, Liu et al. 2017). On the other hand, when data are donated in a real-world setting without a scenario description, individuals might disclose more information about themselves because the privacy risk is less salient (Marreiros et al. 2017). Conducting a field experiment in which participants actually donate their data would not have been possible from an ethical and regulatory standpoint, because putting individual data artificially under the risk of a data leak would violate relevant regulations, such as the General Data Protection Regulation. As more real-world data donation use cases such as coronavirus tracking apps emerge and their users suffer from accidental data leaks, *ex post* natural experiments might allow researchers to glean further insights into revealed user preferences regarding data donations to promote social welfare.

Third, participants indicated their *WDPD* from a specific list of data types to be donated and for two specific domains of social welfare. Because the willingness to disclose data varies with the type of data being disclosed (Phelps et al. 2000, Lim et al. 2018), we expect *WDPD* to be greater the fewer data types are required and the less sensitive the data is. We provide first evidence that the *WDPD* depends on the domain of social welfare by investigating a sustainable environment and health system. However, extant literature gives no empirical guidance that allows us to build assumptions on how *WDPD* might change with other domains of social welfare. Although the disclosure of data for different purposes has been studied in the past (Morse 2007, Pavone and Esposti 2012, Liu et al. 2017), survey designs and data types often vary, which prevents us from drawing conclusions about the role of the donated data's purpose. To the best of our knowledge, our online experiment is one of the first empirical studies to keep the data types constant and vary only the different domains of social welfare. From our results, we would expect that individuals are more likely to donate data the more the promoted social good benefits society at large rather than any individual member of society.

Notwithstanding these limitations, insights from our online experiment extend the research on the disclosure of personal data by investigating data disclosure as a voluntary donation to promote social welfare. Because data donations involve privacy costs without providing personal benefits, individuals have an incentive not to cooperate, which results in the social dilemma of big data. Our results provide first evidence for how individuals donate personal data in a scenario in which a database resembles a public good and must be sufficiently large and diverse to enable technology to promote social welfare. Our results are novel in that they show that individuals would donate their data despite personal privacy costs, uncertainty about whether enough other people are donating their data, and uncertainty about the amount of data required for the database to increase social welfare.

Understanding the drivers and barriers of socially directed data donation is relevant for the research community, but also to legislators and practitioners such as non-profit organization representatives. The COVID-19 pandemic illustrates the high potential of data in promoting public health as a domain of social welfare. However, the severity of the pandemic also underscores the failure of governments to adequately encourage public debate and educate the public on the prosocial use of citizen data before crises. The majority of governmental data collection measures were discussed and implemented in the middle of a global emergency, a time when people may be fearing for their health, the health of others, and the consequences for society. The timing of the discussion on data disclosure may raise ethical concerns because fear favors consent to voluntary and mandatory data disclosure to the state (Hillebrand 2021). To ensure ethical use of citizen data, policy makers and legislators need to address population preferences and understand what factors should be considered when using data to promote social welfare—if data disclosure is voluntary, to create conditions that motivate individual data donation; if data disclosure is mandatory, to create conditions that reflect society's preferences to ensure ethical use (Ali and Bénabou 2020). According to our findings, legislators should particularly focus on the risk of a data leak, the organization that collects and manages the data, and the purpose for which the data will be used. With these insights, we hope to further support non-profit organizations such as the UN, which has been working for years to mobilize citizen data, in designing structures that encourage more individuals to voluntarily donate their data.

4.2 The Role of Fear and Trust when Disclosing Personal Data to Promote Public Health in a Pandemic Crisis

Abstract. During the 2020 pandemic crisis, state surveillance measures violated citizens' privacy rights to track the virus spread. Rather little civic protest resulted—"safety first"? Indeed, many state measures were implemented during the crisis without ever having been discussed in advance of the event of a crisis, which may raise ethical considerations, as individual consent to data disclosure may change while experiencing fear. This paper investigates citizens' consent to voluntary and legally obliging data disclosure to the state and what drives their consent. Results from an online survey conducted with 1,156 respondents during the onset of the crisis in Germany in mid-March 2020 show that (1) fear increases consent to voluntary data disclosure, (2) fear increases consent to legally obliging data disclosure directly and indirectly by fostering distrust in others, and (3) trust in the government increases voluntary and legally obliging data disclosure.

4.2.1 Introduction

In early 2020 the world started to change in the face of the coronavirus. While in certain regions of China the first mass quarantines and the cancellations of the Chinese New Year celebrations have already been ordered in January (Rabin 2020), many Western nations imposed major restrictions especially in March as a response to the exponentially rising infection numbers: Italy locks its borders and closes all schools and universities (Tagesschau 2020a), France introduces a curfew in which citizens are not allowed to leave their homes without a respective certificate (Wachs 2020). US President Trump declares a national state of emergency (DPA 2020) and the Dax faces its highest loss since the September 11 terrorist attacks (Hock 2020). Germany, like many other countries, decrees the drastic restriction of social contacts and closes down gastronomy and certain service companies (Die Deutsche Bundesregierung 2020). Spain even closes all "non-essential businesses" (MDR 2020). In times of crisis, the state is expected to take action. In most Western democracies, governments restricted basic citizens' rights, though little protest resulted; citizens likely were apt to think that security comes first. In a pandemic crisis, different rules seem to apply—but is this the case even for data protection? Although international politicians have addressed the crisis in various ways, one measure was popular: the use of public information to control the spread of the virus. Some states seem to put safety first and insisted on state supervision of all citizens, whereas others relied on voluntary approaches. In Taiwan, for example, people entering the country were monitored by their mobile data to ensure that they were complying with the quarantine. South Korea had authorities record location data of infected people using GPS tracking and compare their movement with credit card transactions and images from video surveillance. Israel allowed its secret service to analyze mobile phone data of millions of users to track movement flows. In Germany, Deutsche Telekom transmitted a one-time set of mobile data to the Robert Koch Institute (RKI) in mid-May to analyze the spread of the virus (Tagesschau 2020b). The German Minister of Health recommended continuous tracking of citizens' location data to identify people who came in contact with infected people. However, after criticism from data protectionists and the German Minister of Justice, a draft for a law to this effect was stopped (Heberlein 2020). Similar to Singapore, Germany then followed a voluntary approach (Senzel 2020). A perquisite for this approach was that users voluntarily disclose their data. At the time this paper was prepared, the discussion in Germany concerned in particular the voluntary sharing of location and health data. The current solution, a Bluetooth-based app without location data, was not considered at that time.

An examination of South Korea, for example, shows that the use of data could indeed have the potential to contain the virus. Although South Korea is democratically governed and, as of this writing, could avoid a lockdown, the spread of the virus is widely controlled. In addition, scientists of the German Academy of Natural Scientists Leopoldina explicitly recommend the use of data (Leopoldina 2020). However, despite its apparent potential, the use of data to contain the virus remains internationally controversial from a data protection standpoint. Data protectionists warn that tracking data during the crisis endangers people's privacy far beyond the pandemic crisis period (Becker 2020). E.g., location data can serve as a diagnostic measure of sensitive individual attributes such as religious or political views and possible health concerns (Gambs et al. 2011). The European Union has therefore classified location data as "personal data" in the General Data Protection Regulation. In the course of the 2020 pandemic crisis, it is striking that a majority of governmental data collection measures are discussed ad hoc and implemented in the middle of a global emergency, a time when people may be fearing for their health, the health of loved ones, and consequences for the public. Data protection advocates warn that governments might use the crisis to realize measures of data collection and state surveillance that they may not have been able to enforce outside the exceptional situation (Chaos Computer Club 2020). Would protests have been greater if these measures were discussed outside the crisis, considering that preferences change when experiencing fear (Loewenstein and Lerner 2003, Weinstein 1980)?

With regard to their safety, citizens face a trade-off: If they make use of the state's voluntary services and thereby disclose their data, the virus can be better controlled without state violation of privacy rights. However, individuals cannot know if a sufficient number of people will comply with these voluntary services to control the virus. Are people willing to take that risk? Or, in times of crisis and fear, do they prefer mandatory data sharing of all citizens to ensure safety? If so, the virus may be better controlled, but the government will violate fundamental privacy rights by surveilling citizens' location without prior individual consent. This paper aims to contribute to a better understanding of what drives preferences of the potentially harmed parties in this trade-off—the citizens. The study is carried out in the context of the 2020 pandemic crisis with German citizens with regard to location data tracking. In this paper I examine how individuals may prefer data sharing over privacy, and in particular whether German citizens are more likely to agree to voluntary or mandatory data sharing to the state if their goal is to ensure safety. I therefore pose the following research question:

> ***RQ***: *How do fear and trust influence the willingness to disclose personal data to the state in order to promote public health in a pandemic crisis?*

4.2.2 Theoretical Background and Research Model

Literature suggests that the individual decision to disclose data is based on a cost–effectiveness analysis, such that data are released if the expected positive outcomes exceed the costs (i.e., the privacy risk). This logic also applies to the disclosure of location data (Dinev and Hart 2006). Researchers have investigated how the willingness to self-disclose location data varies with the nature of the generated benefit. They distinguish between "symbolic" or "hedonic" benefits (e.g., additional values such as better service, personalization of offers) and "utilitarian" benefits (e.g., goods, monetary advantages) (Sun et al. 2015, Xu et al. 2009). However, extant literature on the disclosure of data based on a privacy calculus neglects crucial particularities of a pandemic crisis. First, the benefit a person gains by voluntary disclosing his or her location is uncertain and delayed. In this situation, whether someone gains an advantage from data disclosure depends on the behavior of others (Dawes et al. 1976). In this paper's scenario, the spread of the virus can only be controlled without governmental coercion if a sufficient number of people voluntarily disclose their location. Second, the benefit is of varying value for each person in a pandemic crisis. The added value depends on what negative consequences a person anticipates if the spread of the virus cannot be controlled. These particularities reveal a social dilemma: If all citizens voluntarily disclose their location, the spread of the virus can be controlled better, and government coercion is avoided. However, every citizen has an incentive to deviate and to benefit from virus control without restricting his or her privacy. Without control of the virus, people are worse off than if they had cooperated. State surveillance of location data without prior consent of the citizens would solve this dilemma. However, state surveillance also means the government violates citizens' basic privacy rights. This study builds on literature that takes the perspective of a privacy calculus to analyze the decision to disclose data. However, to examine the extent to which citizens prefer their privacy rights to be violated by the state in a pandemic crisis for the sake of safety, the study also focuses on literature on social dilemmas, especially on psychological factors of decisions in "give-some" dilemmas and public good games with imperfect information and uncertainty.

Uncertainty and Trust. Extensive literature has examined interpersonal factors associated with cooperation in public good dilemmas. One factor of consensus is trust. Individuals who trust others show higher rates of cooperation than individuals with low trust in others (Deutsch 1960, Komorita et al. 1991). Trust is especially relevant in decisions under uncertainty (Yamagashi 2011). Respondents in this survey evaluated their consent to state surveillance with imperfect information and under two types of uncertainty: environmental uncertainty (i.e., uncertainty about the situation and conditions for obtaining the public good) and social uncertainty (i.e., uncertainty about the decisions of others) (Orbell et al. 1988). The current study focuses on social uncertainty. The common favorable outcome will be achieved if the virus spread is better controlled through location tracking without state coercion. Whether control is realized depends on socially uncertain decisions of two groups, fellow citizens and government officials, as it is uncertain whether fellow citizens would consent to voluntary data disclosure and whether government officials would use location data only to actually control the spread of the virus. Considering the role of trust in making decisions under uncertainty, this discussion leads to the following hypotheses about the effect of trust on a citizen's consent to be voluntarily surveilled by the state:

> ***Hypothesis 1a:*** *Interpersonal trust (T_{ip}) increases consent to voluntary data disclosure to the state (C_{vd}).*

> ***Hypothesis 1b:*** *Trust in the government to actually use the data to control the spread of the virus (T_{gov}) increases consent to voluntary data disclosure to the state (C_{vd}).*

A review of the literature also leads to competing hypotheses about the effect of interpersonal trust on the consent to legally obliging data disclosure. People are often willing to accept personal disadvantages and even prefer institutions that monitor cooperation so that the common good can be promoted (Fehr and Gächter 2000, Gürerk et al. 2006). If others are trusted to jointly achieve the control of the virus spread through voluntary cooperation, state coercion becomes obsolete and illegitimate. If others are not trusted, state coercion may be preferred to ensure cooperation and safety.

> ***Hypothesis 2a:*** *Interpersonal trust (T_{ip}) decreases consent to legally obliging data disclosure to the state (C_{od}).*

> ***Hypothesis 2b:*** *Trust in the government to actually use the data to control the spread of the virus (T_{gov}) increases consent to legally obliging data disclosure to the state (C_{od}).*

Payoff Levels and Group Identity. Research in which experimenters have manipulated payoff levels shows that unequal payoffs influence cooperation (Komorita et al. 1993). In a pandemic crisis, payoff levels are determined by the real-world situation, in which payoffs are not only uncertain but also unequal. Individuals benefit in varying degrees from a controlled virus spread. Similarly, the negative consequences for individuals vary if the spread of the virus is not controlled. In the context of the current study, survey responses indicate that fear of the consequences of the novel coronavirus determine the perceived payoff level. When making decisions, people's brains are configured to divide people into "us" and "them" (Greene 2014) and they work in a dual process: fast (i.e., based on gut feeling and intuition) and slow (i.e., analytically and rationally) (Kahneman 2011). Judgment based on gut feeling increases intragroup cooperation but leads to an in-group-preferential bias. People especially judge intuitively in situations with imperfect information and under uncertainty, such as the 2020 pandemic crisis (Tversky and Kahneman 1974). Thus, people may perceive a payoff level differently, depending on which group profits from it. In public good games, too, the willingness to cooperate depends on the group affiliation of the players. If the out-group profits more from a good than its own group, the cooperation rate decreases (Dawes et al. 1976, Parks and Hulbert 1995). The following hypotheses on the influence of unequal payoffs on the consent to surveillance, therefore, differentiate between two groups: the in-group, one's self and closest people, and the out-group, the country's population.

> ***Hypothesis 3a:*** *Fear (F_{in} / F_{out}) increases consent to voluntary data disclosure to the state (C_{vd}). Fear for self and closest people (F_{in}) has a greater impact than fear for the population (F_{out}).*

> ***Hypothesis 3b:*** *Fear (F_{in} / F_{out}) increases consent to legally obliging data disclosure to the state (C_{od}). Fear for self and closest people (F_{in}) has a greater impact than fear for the population (F_{out}).*

The Interplay of Fear and Trust. Literature on cooperation shows an interplay of fear and trust. For example, researchers examined high and low trusters' responses to fear in a public good dilemma and found that when fear is present in a game, people with a high level of trust cooperate more than people with a low level of trust (Parks and Hulbert 1995). However, fear in this research refers to the possibility of not receiving a payoff despite cooperation. In the context of a pandemic crisis, fear rather is an indicator for the perceived consequences if the virus is not controlled. As described, the negative consequences of the novel coronavirus are not only uncertain but also unequal. To cover this particularity, the current study follows the argumentation of the security dilemma, whose original concept has been further developed for current global security challenges (e.g., the cyber security dilemma) (Buchanan 2016, Jervis 1978). The security dilemma suggests that states achieve the highest level of security if all states cooperate, but in the real world they do not, because they have incentives to defect. The more a state fears the consequences of defection, (1) the greater the state's incentive to join a larger entity and (2) the greater its distrust in other states. States that can afford a zero payoff have greater trust in others and cooperate more often. In terms of the pandemic crisis, this means that people who greatly fear the consequences of the novel coronavirus can less afford to let the virus spread, and thus can less afford to trust others and are more inclined to consent to regulated surveillance.

> ***Hypothesis 4a:*** *Fear (F_{in}/ F_{out}) indirectly decreases consent to voluntary data disclosure to the state (C_{vd}) by decreasing interpersonal trust (T_{ip}).*

> ***Hypothesis 4b:*** *Fear (F_{in}/ F_{out}) indirectly increases consent to legally obliging data disclosure to the state (C_{od}) by decreasing interpersonal trust (T_{ip}).*

Figure 8 presents a graphic depiction of the research model.

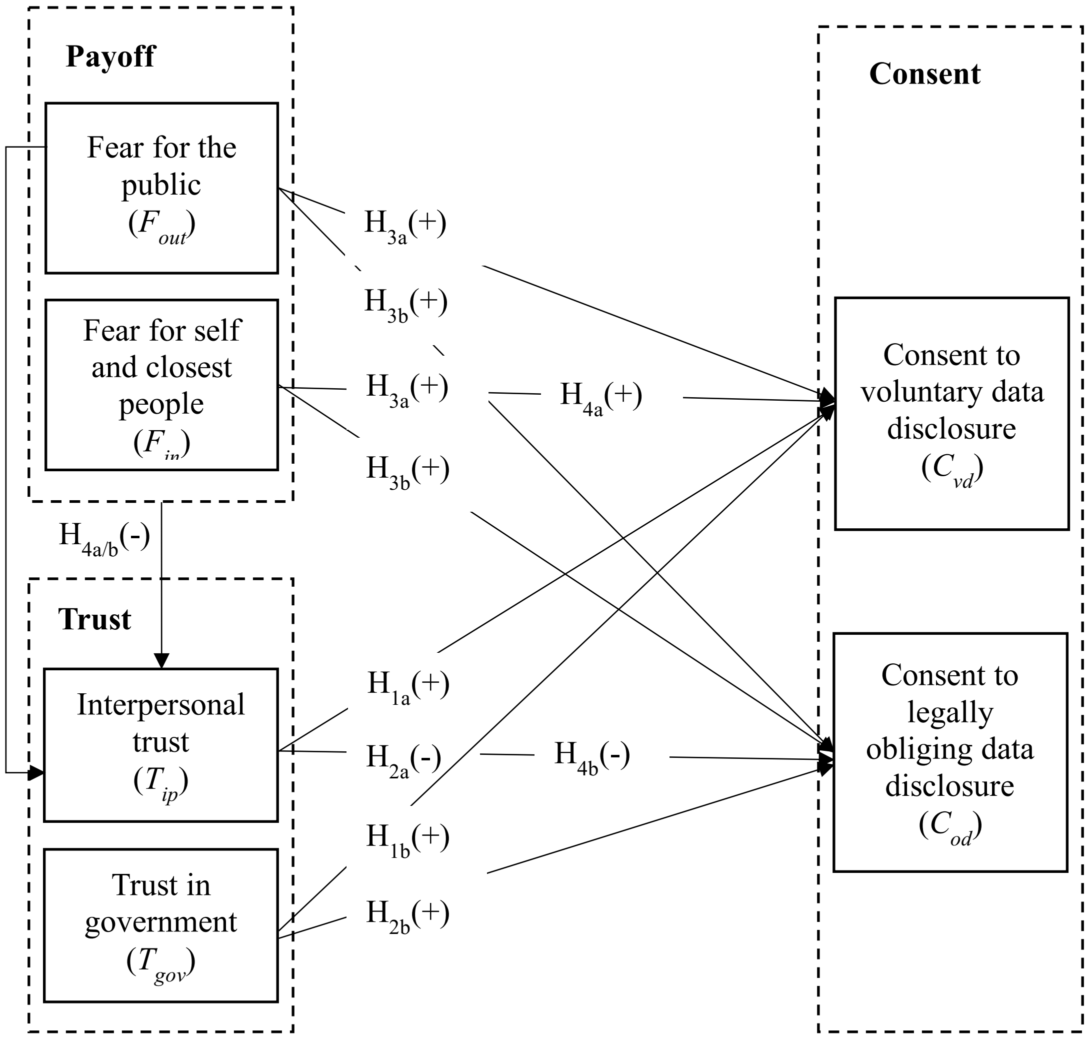


Figure 7. Research Model

4.2.3 Method

Data Collection and Sample Description. The data were collected via an online survey in the period from March 18 to March 29, 2020, when the pandemic crisis in Germany intensified such that the increase in infections changed from moderate to exponential. While the first person in Germany died of COVID-19 on March 8, approx. three weeks later, on March 31, there were already 584 reported deaths (RKI 2020). Also, the number of new infections per day reached the first wave's peak during the survey period on March 28 with 6,294 newly infected persons. There was heated political and public debate on possible government measures. The German government implemented many actual measures during the course of the survey, such as the drastic restriction of social contacts and the closing of gastronomy and selected service businesses on March 22 (Die Deutsche Bundesregierung 2020). The day before the survey launched, it became public that the German mobile network operator Telekom shared a one-time set of mobile phone data of German citizens with the RKI (Tagesschau 2020b). At the time of the survey there was no public discussion about the governmental “Corona-Warn-App” as it exists today. The survey period during the crisis outbreak is crucial to the significance of this study's results. During the outbreak, it was still uncertain what measures the state would conclusively introduce and how great the threat of the novel coronavirus really was to the individual; in short, the period was characterized by uncertainty. After the outbreak phase, participants' responses could be influenced by the extent to which the measures implemented up to that point were effective and what damage the virus actually caused to individuals. The advantage of surveying during the outbreak therefore is that the anticipated benefit of location data to contain the virus is less dependent on country-specific government measures and the development of the crisis. The study results are therefore more general and allow for better implications. Another advantage of surveying during the outbreak is that, due to the increasing state restrictions on civil rights during that period, participants could assume that the government might actually introduce surveillance measures, which contributes to the credibility and realistic nature of the survey content.

The survey respondents were recruited via social media. To obtain a representative sample of the German population, the ad was targeted to all users registered on Facebook and Instagram in Germany. Studies investigating the representativeness of social media samples for the general population provide contradictory results. While Twitter and Facebook users in the UK differ from the general population in terms of age, gender and education, they are representative of values and political behavior (Mellon and Prosser 2017). An evaluation of Facebook advertising to generate a representative sample of Canadians for a health survey concludes that the sample is representative of geography, age and income. However, the sample was over-representative of women and higher levels of education (Shaver et al. 2019). Other scientists compared responses to an online survey on climate change public opinion between two US samples: one was generated with Facebook ads, one based on a high-quality online survey panel. Although the social media sample was not representative of the US population, the responses were mostly identical to those of the high-quality sample (Zhang et al. 2020). Overall, results suggest that using the Facebook Ad Network to recruit participants, despite a potential lack of representativeness, is suitable for querying population-level public opinion.

The call to participate in the survey appeared in various ad formats such as a “sponsored story” and “sponsored post”. The users to whom the ad was displayed were randomly selected. Randomization was implemented by deactivating the Facebook feature of displaying ads optimized for cost efficiency. The survey advertisements were displayed to a total of 40,584 German users (on average 1.15 times per user) on Facebook and Instagram. Of these people, 2,705 clicked on the survey link and were redirected to the survey's introductory text (click rate of 6.67%). 1,253 people have started to actually fill out and 1,156 completed the survey (dropout rate of 7.74%). Participation was voluntary and not compensated. Respondents were randomly assigned to one of two survey versions, which differed only in the dependent variable (C_{vd}/C_{od}). Responses from individuals were excluded from the data set if (1) they answered the survey in less than a minute, (2) answers indicated random clicking (maximum or minimum values selected for all answers), (3) they were under 18 years of age, or (4) they submitted unrealistic answers (e.g., age over 100 years).

In total, 889 participants answered all survey questions without exceptions and irregularities. Data provided by this group serve to test hypotheses 1–4. The sample consists of 62% female, 29% male, and 1% diverse-gendered respondents, with 9% preferring not to answer. The median age of the respondents is 37 years, with the youngest being 18 years and the oldest 75 years. The majority of the respondents has high vocational training (26%) or a school diploma (21%), followed by a graduate degree (17%). 36% of the respondents, in approximately equal parts (between 6% and 9%), reported attaining less than a high school diploma, having attended college, having a bachelor’s degree, or not fitting into any of the answers, and 4% of the participants preferred not to answer. The mean net annual income of the respondents is “15,001€ to 25,000€” (minimum “less than 5,000€”, maximum “more than 100,000€”). Respondents indicated their political views on a slider from 1 (“left”) to 20 (“right”). The mean political view is 8, thus skewing slightly more left.

Measures. All independent (T_{ip}, T_{gov}, F_{in}, F_{out}) and dependent (C_{vd}, C_{od}) variables were measured using a 1–20 slider (see Appendix B). The language to measure the variables fear, consent, and trust in government is based on Awad et al.'s German question items in the Moral Machine Experiment (2018). These items used the wording "To what extent ..." on a slider with extreme point labels of "very little" and "very much" and were modified from the original version to fit the context of a pandemic crisis (pretested with five people). The variables on interpersonal trust (T_{ip}) and political views were collected using the original wording of the German socio-economic panel. The control variables for gender, education, net annual income, and age were adopted from Awad et al. (2018) without any modifications. To control for possible influences by daily events, timing of participation, coded in 12-hour intervals from 1 to 20, serves as an additional control variable.

4.2.4 Data Analysis and Results

Measurement Model. Ordinary least squares (OLS) regressions were used to test hypotheses 1—4. Data were checked for various parameters before performing the regressions. None of the regression models have autocorrelation based on values of the Durbin–Watson statistic. Pearson correlation coefficients used to check for possible multicollinearity indicated that all variable correlation coefficients are lower than .7; the highest correlation (.649) manifested between fear for self and loved ones and fear for the population. All other correlations are below .355. Graphical visualization confirmed variance equality and normal distribution of the residuals. Two regression models served to test hypotheses 1–3: Model 1 uses consent to voluntary data disclosure (C_{vd}), and Model 2 uses consent to state surveillance (C_{od}) as the dependent variable. C is a vector of variables, including age, education, income, political views, gender, and day of measurement as baseline conditions.

$$\boldsymbol{C_{vd}} = \beta_0 + \beta_1 F_{in} + \beta_2 F_{out} + \beta_3 T_{ip} + \beta_4 T_{gov} + \beta_5 C + \varepsilon. \qquad \text{(Model 1)}$$

$$\boldsymbol{C_{od}} = \beta_0 + \beta_1 F_{in} + \beta_2 F_{out} + \beta_3 T_{ip} + \beta_4 T_{gov} + \beta_5 C + \varepsilon. \qquad \text{(Model 2)}$$

A third set of regression models served as a mediation analysis to test Hypotheses 4a and 4b. Mediation is considered present when the following four conditions are met (MacKinnon et al. 2007): First, the fear variable (F_{in}/ F_{out}) has a significant effect on consent to voluntary data disclosure (C_{vd}) in Equation 1. Second, the fear variable (F_{in}/

F_{out}) has a significant effect on the mediator variable interpersonal trust (T_{ip}) in Equation 2. Third, in Equation 3 (identical to Model 1) the mediator variable Tip has a significant effect on C_{vd}, and fourth, the coefficient of β_1 and the coefficient of β_2 must be smaller in absolute terms in Equation 3 than in Equation 1. The mediation for consent to state surveillance (C_{od}) is identified analogously (Equation 3 identical to Model 2).

$$C_{vd} = \beta_0 + \beta_1 \boldsymbol{F_{in}} + \beta_2 \boldsymbol{F_{out}} + \beta_3 T_{gov} + \beta_4 C + \varepsilon. \quad (1)$$

$$T_{ip} = \beta_0 + \beta_1 \boldsymbol{F_{in}} + \beta_2 \boldsymbol{F_{out}} + \beta_3 T_{gov} + \beta_4 C + \varepsilon. \quad (2)$$

$$\boldsymbol{C_{vd}} = \beta_0 + \beta_1 F_{in} + \beta_2 F_{out} + \beta_3 T_{ip} + \beta_4 T_{gov} + \beta_5 C + \varepsilon. \quad (3)$$

Structural Model and Hypotheses Testing. Table 6 summarizes the OLS testing results. H1a predicted a positive relationship of interpersonal trust (T_{ip}) and consent to voluntary data disclosure. Regression results are not significant; thus, H1a is not supported. By contrast, interpersonal trust and consent to state surveillance show a significant, negative relationship, in support of H2a. Trust in government significantly increases both consent to voluntary data disclosure and consent to state surveillance, in support of H1b and H2b. Fear for self and closest people significantly increases consent to voluntary data disclosure, while fear for the public does not. Although H3a suggested an influence of fear for both the in-group and the out-group, the influence of in-group fear was expected to be stronger. Thus, H3a is considered supported. In line with H3b, fear for self and closest people and fear for the public significantly increase consent to legally obliging data disclosure; however, fear for the public has a higher impact than fear for self and closest people, thus offering only partial support for H3b.

Table 6. Results of OLS Analyses

	Model 1	**Model 2**	**Set of Models for Mediation Analysis**			
			mediation on *C_vd*		mediation on *C_od*	
	dv: C_vd	*dv: C_od*	*equation 1* *dv: C_vd*	*equation 2* *dv: T_ip*	*equation 1* *dv: C_od*	*equation 2* *dv: T_ip*
Intercept	1.104 (2.115)	1.784 (1.917)	1.208 (2.051)	**7.627***** (1.513)	3.189 (1.850)	**8.802***** (1.411)
Fear for outgroup	0.135 (0.086)	**0.341***** (0.082)	0.137 (0.085)	**-0.138*** (0.063)	**0.356***** (0.082)	-0.095 (0.062)
Fear for ingroup	**0.244**** (0.079)	**0.157*** (0.073)	**0.247**** (0.077)	**-0.257***** (0.057)	**0.194**** (0.072)	**-0.232***** (0.055)
Interper-sonal trust	-0.014 (0.066)	**-0.160**** (0.062)				
Trust in government	**0.372***** (0.056)	**0.143***** (0.033)	**0.372***** (0.056)	-0.011 (0.041)	**0.141***** (0.033)	0.017 (0.025)
Age	0.033 (0.025)	**0.056*** (0.025)	0.033 (0.025)	-0.032 (0.018)	**0.056*** (0.025)	-0.001 (0.019)
Education	0.105 (0.200)	-0.231 (0.178)	0.105 (0.200)	0,010 (0.148)	-0.275 (0.178)	0.277 (0.136)
Gender	-0.072 (0.686)	0.134 (0.639)	-0.081 (0.684)	0.652 (0.505)	0.146 (0.643)	-0.074 (0.490)
Income	-0.079 (0.176)	-0.129 (0.161)	-0.083 (0.175)	**0.306*** (0.129)	-0.125 (0.162)	-0.022 (0.123)
Political view	0.131 (0.081)	0.102 (0.075)	0.132 (0.081)	-0.069 (0.059)	0.107 (0.075)	-0.030 (0.057)
Day	-0.068 (0.055)	**-0.119*** (0.055)	-0.067 (0.055)	-0.051 (0.041)	**-1.09*** (0.055)	-0.061 (0.042)

Notes: Unstandardized coefficients and standard deviations are shown. p-values are reported as follows: * $p < .05$; ** $p < .01$; *** $p < .001$. Dashed lines indicate no significance. All models are estimated with an OLS linear regression. Model 1 and mediation analysis on C_{vd}: N_1=430, Model 2 and mediation analysis on C_{od}: N_2=459.

Mediation analyses using several regressions according to MacKinnon et al. (2007) offer further results. H4a predicted that fear would indirectly decrease consent to voluntary data disclosure by decreasing interpersonal trust. As interpersonal trust has no significant impact on consent to voluntary data disclosure, mediation according to H4a is not supported. H4b predicted that fear would indirectly increase consent to state surveillance by decreasing interpersonal trust. For fear for self and closest people, all four conditions are met. First, fear (F_{in}) increases consent to state surveillance in Equation 1 (β_1=.194, p=.007). Second, fear (F_{in}) decreases interpersonal trust in Equation 2 (β_1=.232, p<.001). Third, interpersonal trust decreases consent to state surveillance in Equation 3 (β_1=.160, p=.010), and fourth, β_1 is smaller in Equitation 3 (Model 2) than in Equitation 1. Thus, fear (F_{in}) indirectly increases consent to state surveillance by decreasing interpersonal trust. Fear for the public does not indirectly increase consent to state surveillance by decreasing trust, as condition 2 is not met (β_2=-.095, p=.127). Therefore, mediation according to H4b is supported for in-group fear. Figure 9 summarizes the significant variable relationships.

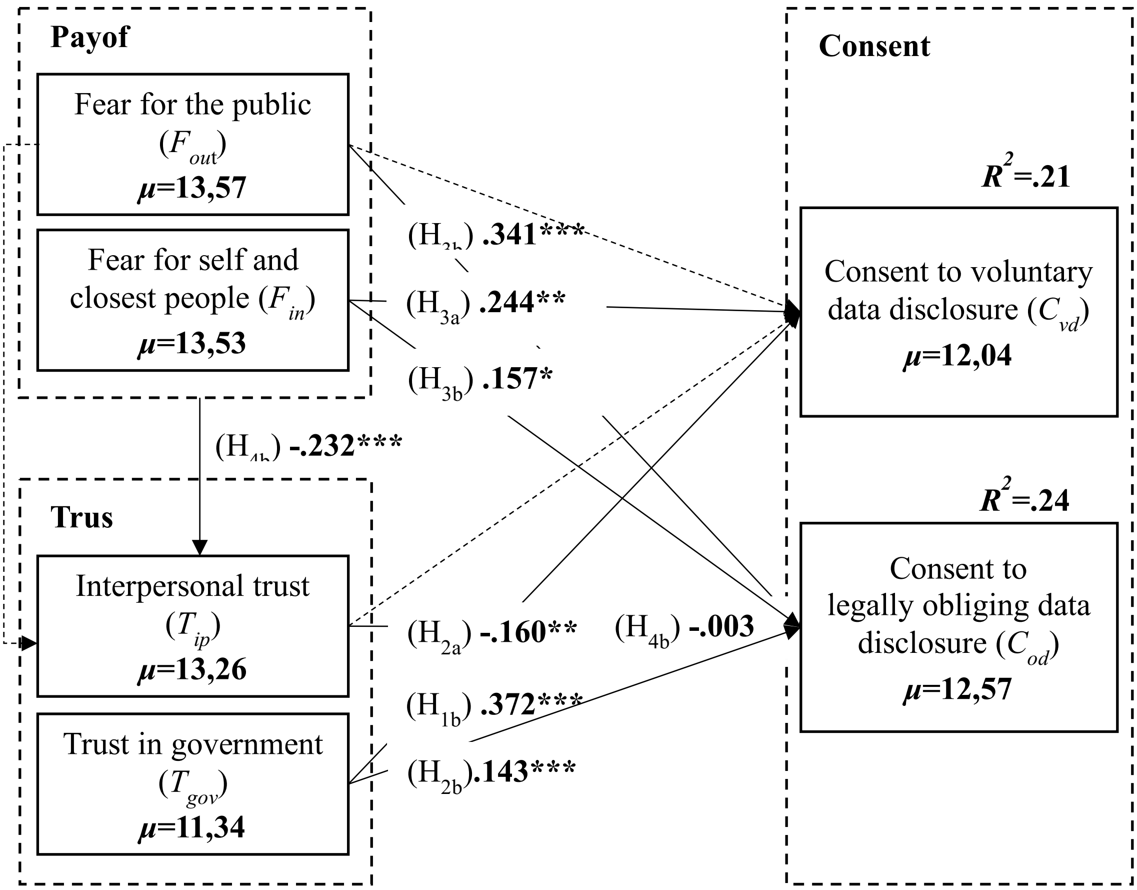


Figure 8. Summary of hypotheses testing results. *Notes:* Goodness of fit, mean, and unstandardized significant coefficients are shown. p-values are reported as follows: * p < .05; ** p < .01; *** p < .001. Dashed lines indicate no significance.

4.2.5 Discussion

The regression results confirm H1b, H2a, H2b, H3a and partially H3b and H4b. In summary, the main testing results are: (1) higher interpersonal trust is associated with less consent to voluntary data disclosure to the state, (2) trust in the government to actually use the data to control the virus spread increases both, consent to voluntary and mandatory data disclosure to the state, (3) fear for self and closest people increases consent to voluntary data disclosure, but fear for the public does not, (4) both, in-group and out-group fear increase consent to legally obliging data disclosure to the state, (5) in-group fear further increases consent to state surveillance indirectly by decreasing interpersonal trust.

Limitations of the results stem from the country-specific survey. Although it is beneficial that data were collected during the outbreak of a crisis, specific daily events in Germany and cultural particularities such as the statutory health insurance system might have influenced the results. Moreover, results would have been more conclusive if the survey had additionally been conducted before the pandemic. This would allow a direct comparison of the fear and trust levels of the two survey dates and would provide clear insights of how consent preferences change while experiencing fear. It may be useful to conduct a repeating survey after the pandemic has abated, but it would remain unclear how responses would be affected by the lasting shock and country-specific measures. In addition, data are based on stated rather than revealed preferences, i.e., there may be discrepancies in the results if people actually had to share their location data. For ethical reasons, it was deliberately avoided to ask individuals to actually disclose their location, as their data would not have actually been used to contain the coronavirus.

Despite those limitations, the findings indicate that the perception of fear affects how people decide on sharing their personal data in a global crisis. It is therefore ethically questionable when people have to make the decision to disclose personal data within a crisis. Governmental officials should initiate the discussion about the handling of personal data in the context of crisis management in advance.

In fact, there have been several stakeholders who have called for a planned approach to handle personal data in crisis management in recent years. International scientists have dealt with the trade-off between security and privacy in crises in various studies. The studies often referred to terrorist crises and disaster control, but the results and political implications can easily be transferred to health crises. For example, Davis and Silver (2004) find that a threat to national or personal security contributes significantly to people renouncing their civil rights. The greater the threat, the less people support civil democratic freedom. Pavone and Esposti (2012) add that public opinion on surveillance technology is influenced not only by the need for security, but also by the context in which the surveillance technology is implemented. In an exploratory study of the willingness of German citizens to reduce their online privacy in favor of security in times of crisis, Reuter et al. (2016) identify a cooperative group that would only do so at certain conditions. Researchers further suggest that measures concerning security and privacy should be decided with some time lag from the crisis itself. If not, overhasty decisions might unnecessarily restrict the freedom of citizens (Gethmann 1996, Orbell 1988, Reuter 2016). Despite varying methods and contexts, existing research results support those of this study. The coronavirus-induced crisis is a special situation in which decisions are potentially made differently than before or after the crisis.

Parts of the political arena have pushed the discussion about the protection of privacy in recent years. For example, the European Union invested billions of euros in security research in the early 2000s (European Commission 2004a, European Commission 2004b). These investments included the research project PRISMS, which ran from 2012 to 2015 and conducted a comprehensive survey of public opinion on the trade-off between privacy and security. The aim of the project was to formulate a decision-support-system to guide the ethical political handling of the trade-off (European Commission 2020a). Nonetheless, there has been no uniform European regulation at the outbreak of the corona crisis. In Germany, too, some politicians recognized the importance of data privacy ahead of the crisis, including Volker Kauder, the parliamentary party leader of the CDU, Stefan Brink, the state data protection commissioner, and Sabine Leutheusser-Schnarrenberger, the federal minister of justice. Also Burkhard Hirsch and Gerhart Baum have been fighting for the protection of basic privacy rights and for a surveillance-free society for many years (e.g., Kurz 2020). But in Germany, too, there has been no pre-determined regulation on how personal data may be used to foster security in the event of a crisis—yet the 2007 LÜKEX report has even identified corresponding deficiencies. The report is the result of a nationwide pandemic crisis management audit with the aim of optimizing governmental and public crisis management. The report identifies an extensive need for action in the area of "prevention" and demands a specification of legal provisions and exception regulations. In 2007, the handling of data had not been subject of the report. However, when concretizing prevention measures in response to the report, policymakers could easily have taken the handling of data into account in the following years. It remains ambiguous why the German government not only failed to respond to identified shortcomings, but also kept the report secret for a considerable time.

In contrast to other countries, Germany ultimately refrained from collecting personal data and relied on a voluntary solution based on the “Corona-Warn-App”. However, it is a fact that monitoring of location data was at least considered. And indeed, in the middle of the second infection cycle, voices from industry and politics are once again calling for restrictions on data protection in order to make the “Corna-Warn-App” more effective. As Michael Hüther, Director of the Institute of the German Economy, says, "It is difficult to understand that while many basic rights are naturally infringed upon in the fight against the pandemic, data protection becomes a sacred cow“ (Neuerer et al. 2020). Other politicians like Dorothee Bär and Dieter Janecek prefer to maintain the population's willingness to cooperate through trust in the government. According to the results of this study, this might be a winning strategy: trusting the government to use the data correctly increases the willingness to share data by using voluntary solutions. If enough people make use of the voluntary offer, the virus spread might be controlled without violating individual privacy. In any case, the resurgent discussion reinforces the importance of the present results.

Overall, exceptional governmental power in a crisis is reasonable in terms of national security measures. A crisis is an extreme situation in which restrictions and violations of personal rights may under certain conditions be appropriate to protect the public. Restrictions may affect economic, cultural and private domains, including the restriction of privacy through the use of personal data. Nevertheless, the results of this study illustrate—in light of relevant studies from other disciplines—that the context in which decisions to restrict privacy are made matters significantly. Decisions in the trade-off of security and privacy must not be forced in the middle of a crisis, both on a political and individual level.

4.3.6 Conclusion

This paper examined the role of fear and trust in consenting to disclose data to the state. During the 2020 pandemic crisis many states proposed data collection measures to contain the coronavirus without ever having discussed these measures transparently in advance. The timing of the governmental data collection could imply ethical concerns, as individual consent might change while experiencing fear. I conducted a survey during the outbreak of the 2020 pandemic in Germany in mid-March. Results show that fear indeed correlates with consent: Voluntary data disclosure depends on how anxious people are about themselves and their loved ones. When consenting to legally obliging data disclosure, fear plays an even greater role. Not only does fear for oneself, loved ones, and the public increase the consent to legally obliging data disclosure, but it also promotes consent by fostering distrust in others.

Despite some limitations, the results allow the conclusion that fear for oneself and others, as well as trust in others and in the state, play an important role in a global health crisis when it comes to disclosing personal data. In Germany, location tracking was hotly debated, but ultimately not carried out. The initial discussion, the data collection measures in other countries and the insights of this paper, however, show the need for defining how personal data shall be handled in crisis situations. If not, the state might violate important individual privacy rights. The public should be involved in this discussion in advance, not in the midst of a crisis while experiencing fear. The findings of this paper contribute to a better understanding of the relevance of timing when states collect personal data. Politicians and researchers should take a closer look at the various factors that can influence the citizens' consent to data disclosure in crises so that regulators can handle and collect personal data in the public's best interest.

A follow-up study is currently in progress and will compare the levels of fear, trust and consent to voluntary and mandatory disclosure of personal data during the first and second infection cycle of the coronavirus. The corresponding online experiment has been conducted at the end of October 2020 and contained identical questions as in March 2020—with one crucial extension: Participants have randomly been primed on content of the recent public debate on how data shall be used in order to control the corona virus spread in Germany. Differences between the experimental groups will allow to draw conclusions as to whether the recent debate has changed citizens' consent to data sharing in the context of a pandemic crisis.

4.3 "KlimaKarl" — A Chatbot to Promote Employees' Climate-Friendly Behavior in an Office Setting

Abstract. Environmental protection is a central challenge these days. At the same time, digital technologies have experienced a tremendous technological progress in recent years and their potential to support firms' sustainability strategies and corporate social responsibility efforts are intensively discussed in research and practice alike. We propose chatbots as a promising technology to promote the climate-friendly behavior of employees. Following a Design Science Research (DSR) procedure, we develop a chatbot prototype called "KlimaKarl" to sensitize the workforce to behave in a more environmentally-conscious way in the everyday office life. In a demonstration and first evaluation of the prototype we could show that chatbots may be a suitable instrument to promote employees' eco-friendly behavior. With this research we contribute to the discussion of how chatbots may be purposefully used within organizations and how digital technologies in general may help to promote sustainability in organizations.

4.3.1 Introduction

Environmental and climate protection are crucial challenges of our time. The UN recognizes the importance of these challenges as part of the Agenda 2030, which was passed by the member states in 2015 (UNGA 2015). The core of the Agenda 2030 are 17 global goals—the SDGs—which are operationalized by 169 targets. With regard to the economic scope for action, environmental and climate protection are particularly represented by SDG 12, "Responsible Consumption and Production", and SDG 13, "Climate Action" (UNGA 2015, Vinuesa et al. 2020).

In economics, recent years have been decisively marked by advances in the field of innovative digital technologies. New technologies like artificial intelligence (AI) are amongst others increasingly changing today's markets (Acemoglu and Restrepo 2018) and employees' skill requirements (Brynjolfsson and McAfee 2014). Given the little time left to reach the SDGs by 2030, enterprises should harness the disruptive potential of digital technologies to meet their corporate social responsibility and to support the achievement of the SDGs. This concern has also reached the public. A movement of scientists, practitioners, and entrepreneurs has emerged under banners like "AI4Good" and “Tech4Good”, which call for the use and development of digital technologies considering their ecological and social contribution (e.g., AI4Good Global Summit 2020, Accenture 2020, Stremming 2020). The question of how data and digital technologies can contribute to the achievement and measurement of SDG 12 and SDG 13 is increasingly compelling.

Innovative technologies comprise various solutions and tools. Their possible application fields to promote sustainability are correspondingly manifold (e.g., Dedrick 2010, Schneider 2019). Vinuesa et al. (2020) performed a consensus-based expert elicitation process and found that AI may enable 13 targets and inhibit 4 targets across the SDGs 12 and 13, e.g., by supporting low-carbon energy systems, high energy efficiency, efficient supply chains and data reporting (International Energy Agency 2017, Vinuesa et al. 2016, WEF 2018). In line with the increasing popularity of the Industrie 4.0 movement, more and more enterprises consider using technological innovations such as blockchain, IoT or additive manufacturing, while their awareness for environmental sustainability is simultaneously on the rise (Dedrick 2010, Schneider 2019). However, the extent to which companies use such technologies to align their business activities with climate and environmental protection goals is still largely opaque. One promising technology that has attracted a lot of attention from practitioners in recent years are chatbots. In a corporate context, chatbots have multiple uses for external communication purposes (e.g., customer service, sales, marketing), and for internal communication promotion (e.g., employee training, knowledge management) (Meyer von Wolff et al. 2019).

Due to their interactive and communicative nature (cf. Brandtzaeg and Følstad 2017), we assume that chatbots are particularly effective in encouraging employees to adopt climate-friendly behavior in their everyday office life. However, the use of chatbots to promote sustainability within companies has not been in the center of research so far. In this paper, we therefore strive to design and develop a chatbot that supports the "green behavior" (Fraunhofer IAO 2014) of employees. The use of a chatbot to motivate climate-friendly behavior is particularly promising for two reasons. First, human behavior is the main source of negative environmental influences, and hence, the most important mechanism for achieving ecological sustainability (Osbaldiston and Schott 2012, Steg and Vlek 2009, Zhao et al. 2017). Second, a company cannot successfully implement its sustainability strategy without the commitment of its employees. A chatbot could familiarize employees with sustainability measures and trigger behaviors in a playful way. In addition, while interacting with the chatbot, users may also contribute their own ideas for improved climate protection inside their company. This way, they can actively participate in the creation of a sustainability strategy, which increases their receptiveness to change when the strategy is subsequently implemented.

This paper illustrates how a chatbot—as a representative for digital technologies—can be used to reach environmental and climate protection goals within an enterprise. We pose the following research question to guide our DSR project:

> ***RQ:*** *What can a chatbot to promote employees' climate-friendly behavior in everyday office life look like?*

The paper intends to motivate researchers to develop creative ways for using digital technologies for environmental protection and is structured as follows: we first provide theoretical foundations. Subsequently, we show the research methodology and the requirements on our prototype. After a description of the prototype development, demonstration and first evaluation, the paper concludes with a discussion and outlook.

4.3.2 Foundations and Related Work

Digital Technologies and Environmental Sustainability. In the recent past, enterprises have increasingly shown interest in the effects of information technology on the environment, while their awareness regarding social and environmental challenges has risen tremendously (Dedrick 2010, Schneider 2019). In this respect, environmental sustainability is seen as an essential feature of corporate social responsibility (CSR) these days (Dedrick 2010). According to McWilliams et al. (2006, p. 1) CSR can be defined as "situations where the firm goes beyond compliance and engages in actions that appear to further some social good, beyond the interests of the firm and that which is required by law". On this occasion, digital technologies are judged to be major drivers for environmental sustainability and promoting green behavior within the workforce (Knaut 2017, Seele and Lock 2017).

For instance, Schneider (2019) discusses the impact of digital technologies (AI, IoT, additive manufacturing, digital twins, augmented reality, blockchain, digital platforms) on environmental sustainability from a general perspective and outlines their potential contributions. Hence, the value propositions associated with digital technologies are an increase of transparency and awareness as well as a reduction of consumption in particular (cf. Schneider 2019). The impact of information technology on the environment is specified by Berkhout and Hertin (2004) in more detail, who differentiate between “direct” (e.g., reduced pollution), “indirect” (e.g., substitution of materials by information goods) as well as “structural and behavioral” effects (e.g., changes in peoples’ lifestyle or structural changes in the economy). Similar thoughts can be found in Li and Found (2017), who propose a series of environmental benefits caused by digital technologies. Further, they uncover and explain main terms that are commonly mentioned in the field of environmental sustainability, such as Eco-Efficient Services, Servitisation or Product-Services System (cf. Li and Found 2017).

Albareda and Hajikhani (2019) perform a literature review on innovation for sustainability (IfS) and identify five major research streams, namely “strategic”, “operational”, “organizational”, “collaborative” and “systematic” IfS. The question as to what degree the digitalization of the production floor affects sustainability in German and Chinese industries is dealt with by Beier et al. (2017). The authors receive indicators that an improved resource efficiency and the intensified use of renewable energy sources are in fact enabled by digital technologies (cf. Beier et al. 2017). Further, Demartini et al. (2019) develop a conceptual framework to specify the importance of digital technologies for the enterprise success dimensions “productivity”, “resilience” and “sustainability”. More, they present the use case of two companies, which both reached improvements in resource efficiency and productivity by help of digital technologies and sustainability strategies (cf. Demartini et al. 2019).

Basic Functioning of Chatbots. While the benefits of digital technologies on environmental sustainability are broadly recognized, the role of chatbots to induce a sustainable environmental behavior within the workforce is an under-researched topic yet. A chatbot is a “computer program” that is able to hold “back-and-forth” conversations (Power et al. 2019, p. 3) “with human beings” by help of Natural Language Speech (Abdul-Kader and Woods 2015, p. 72). The typical interaction between the chatbot and the user is among others described by Stucki et al. (2018), who differentiate between the following six steps: The conversation is usually triggered by the customer, who enters a request (Step 1). The chatbot then performs a “data cleansing” activity to mitigate typing errors or eliminate punctuation marks in the user input (Step 2). Afterwards, techniques of syntactical (focusing the sentence structure) and semantical (focusing the meaning of the words) Natural Language Processing (NLP) come to use (e.g., sentence splitting, stemming, tokenization) to prepare the input for further processing (Step 3). The next step (Step 4) is about extracting users’ intent from the pre-processed input (intent matching). Depending on the chatbot implementation, pattern-matching, algorithms or neuronal networks are applied (Kaiser et al. 2019, Kassibgi 2017). After that, a suitable response is retrieved from the chatbot’s knowledge base (Step 5) (Stucki et al. 2018). The response is then passed to the user (Step 6). Figure 10 shows this basic interaction flow with a chatbot according to Stucki et al. (2018).

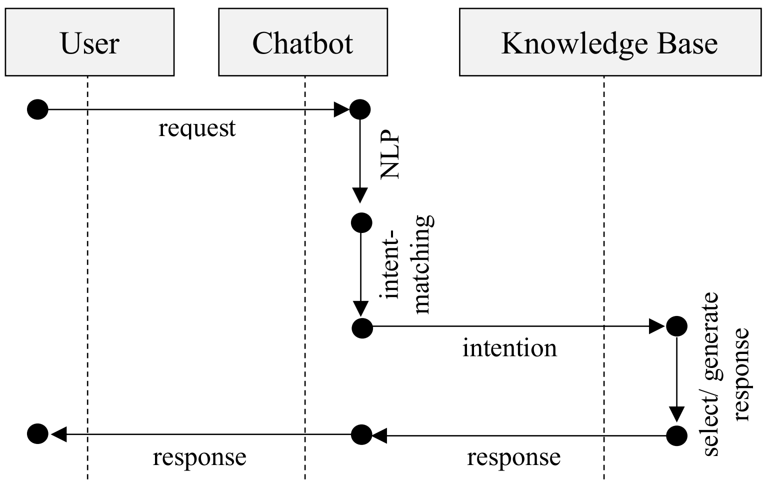


Figure 10. Interaction flow between the user and the chatbot, modified from Stucki et al. (2018).

Generally, terms such as “chatterbot”, “virtual assistant” or “conversational agent” are used as synonyms for “chatbot” in literature (Klopfenstein et al. 2017). While the expression "chatterbot" describes early computer programs that have been built to simulate human-to-human conversations, the term "virtual assistant" addresses programs that actually create "value" and deliver services for users, e.g., in e-commerce, e-government or education (Klopfenstein et al. 2017, Shawar and Atwell 2007). "Spoken dialogue systems" were developed in the 80's and only recently "smart assistants" such as Apple's Siri or Microsoft's Cortana came up (Klopfenstein et al. 2017, Shawar and Atwell 2007). Accordingly, new terms describing the "chatbot" phenomenon evolved in the recent past alongside the technological progress.

Entrepreneurial Chatbot Usage for Internal and External Communication. The first chatbot ELIZA, which was created by Joseph Weizenbaum in the '60s (Weizenbaum 1966), simulated a psychotherapist and triggered the search for further beneficial application fields for chatbots (cf. Dale 2016). These days, chatbots are used in various functional areas for internal as well as external communication purposes. In terms of an organization's external communication with consumers, many companies and institutions (e.g., administration) have introduced chatbots as a means to support the customer service (e.g., Gorelov 2016). For example, Toshiba could reduce the number of support calls by 30-50% that way and customers appreciate a chatbot's 24hrs a day availability, which strongly contributes to customer satisfaction (Drift 2018, Gorelov 2016, Living Actor 2017). Meanwhile, many customers even prefer to use chatbots for contacting a company instead of traditional communication channels (e.g., telephone, email) (cf. Drift 2018). Horzyk et al. (2009) point out that chatbots may also increase the "customer experience" during online shopping, while the Bank of America uses chatbots to analyze customers' behavior in order to provide consumer-specific offerings (Kusber 2017). Other application fields for chatbots comprise e-government (e.g., Sandoval-Almazán and Gutiérrez-Alonso 2009), education (e.g., Goda et al. 2014), healthcare (e.g., Bickmore et al. 2010, Comendador et al. 2015), and law (e.g., Dale 2019) amongst others.

Chatbots are increasingly discussed to support the internal communication within an organization as well. Hence, according to a recent interview study by Meyer von Wolff et al. (2019), practitioners see internal/external support, human resources, purchase/sales, maintenance, (employee) self-service, employee training and knowledge management as promising areas for chatbots to foster the communication within the workforce (e.g., Kowalski et al. 2013, Piyatumrong et al. 2018, Zumstein and Hundertmark 2017). For example, Bihade et al. (2018) present the case of the Internet retailer Overstock and their chatbot Mila, which supports the internal processing of employees' requests for sick leave and facilitates rescheduling of personnel capacities (cf. Rajdev 2017). More, the use of chatbots in the course of IT service management is frequently often described in literature (cf. Kottorp and Jäderberg 2017, Raut 2018). Chatbots are even used in terms of accounting, e.g., the chatbot Pegg[15] as introduced by SAGE (Henrich 2017). Finally, Tavanapour and Bittner (2018) propose the innovation management process to be purposefully supported by chatbots, as these can be used to guide the idea specification activity.

Though, the use of chatbots in the course of environmental sustainability efforts of companies is not in the center of current research so far. Hence, we address this research gap by the design of a prototype called KlimaKarl. In this paper, we specify how the KlimaKarl prototype may look like to promote environmental behavior within the workforce. While few chatbots for supporting environmental education, e.g., AluxBot for school-age children (cf. Peniche-Avilés et al., 2016) or encouraging sustainable mobility behavior exist (cf. Diederich et al., 2019), our target audience are the company employees in particular.

4.3.3 Methodology and Research Design

To develop a prototype of our chatbot, KlimaKarl, we conduct a typical DSR project (cf. Gregor and Hevner 2013, Hevner et al. 2004) and follow the common procedure of Peffers et al. (2007). Figure 11 summarizes the steps of the design procedure.

[15] https://www.sage.com/en-gb/products/pegg/

1. Problem	**2. Objectives of a Solution**	**3. Design & Development**	**4. Demonstration**	**5. Evaluation**	**6. Communication**
Digital technologies are not yet sufficiently used to promote CSR. Currently, there is a lack of chatbots that motivate green office behavior in special.	Requirements on a chatbot prototype to promote green office behavior are formulated.	An iOS/Android chatbot prototype is designed and implemented.	By referring to an employee contest scenario, the chatbot's functionality is demonstrated and exemplified.	The usefulness, applicability and usability of the prototype are evaluated in field studies.	The app will be rolled out at partner companies and the German B2B market.

: Focus of this paper
: In progress
: Future Work
process iteration

Figure 11. DSR procedure modified from Peffers et al. (2007).

The problem statement (Step 1) has been formulated in the introduction. In Step 2 ("Objectives of a Solution"), we derive requirements on our prototype (1) by reviewing corresponding fields of literature, (2) by examining the German B2B market for similar chatbots, (3) by discussing the chatbot usage in an office environment with company representatives at a workshop, and (4) by conducting a survey at a city fair where we asked office employees about their requirements for KlimaKarl. The resulting requirements were prioritized in order to define a feasible set of key design requirements for the initial prototype. This prioritization was done by assessing possible functionalities in terms of their implementation efforts and a feedback talk with the company representatives who attended the abovementioned workshop. Step 3 ("Design & Development") includes design-related decisions (e.g., the creation of the prototype's general structure) as well as the implementation of the prototype by help of suitable frameworks and open source solutions. The next step (Step 4, "Demonstration") deals with the demonstration of the prototype at two companies from the energy and retail sector to assess its general practicality. In Step 5 ("Evaluation") the usefulness, applicability and usability (cf. Hevner et al. 2004) of the prototype are to be analyzed in more-depth in a larger field study. Subsequent to the evaluation, the app will be revised and further optimized before launching a large-scale roll-out across German companies.

The purpose of this research is to contribute to the knowledge base (cf. Gregor and Hevner 2013, Hevner et al. 2004) of using chatbots to promote green office behavior of the workforce. Our research generates "prescriptive knowledge" in the sense of Gregor and Hevner (2013) since we create a running prototype that is designed on the basis of previously and carefully defined requirements.

4.3.4 Objectives of a Solution

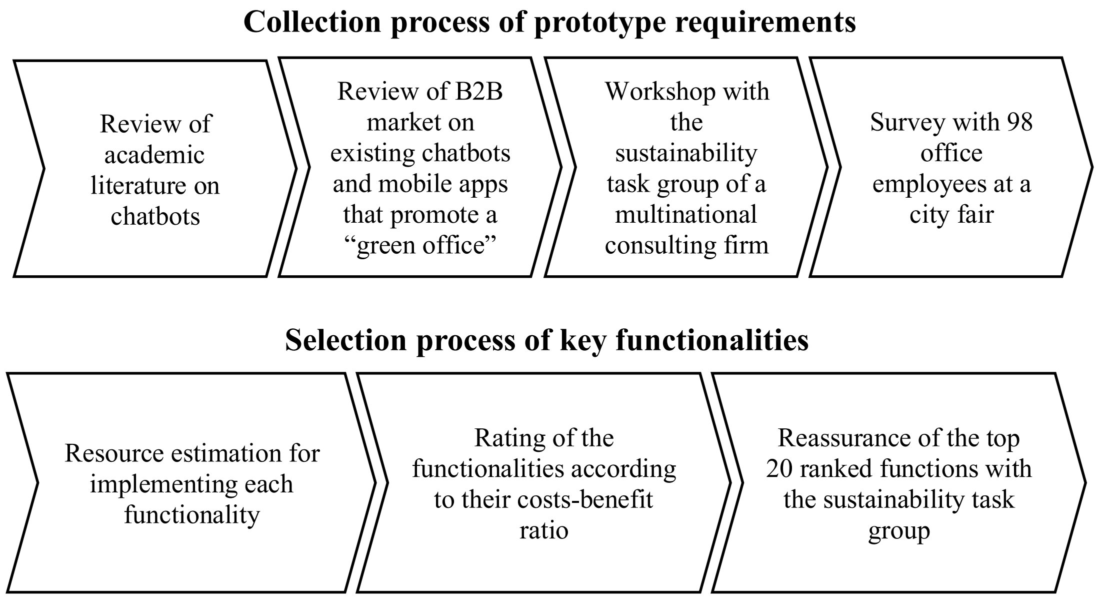


Figure 9. Collection and selection process of functionalities and requirements.

To determine specific requirements for the chatbot's design and functionalities, we considered different perspectives from research, market, customer, and user in a four-step process. In another three steps, we worked in an interdisciplinary group consisting of the project initiators, a developer, and company representatives to break down the multitude of suggestions and ideas into the core requirements of the prototype. Figure 12 visualizes the collection and selection process.

To derive specific design requirements, we first scrutinized the literature about chatbot design at first to find generally acknowledged design propositions concerning the implementation of chatbots (e.g., Berry et al. 2004, Gennermann and Hack 2011, Hill et al. 2015, Johannsen et al. 2018). Second, we searched the B2B market for similar digital technologies and chatbots. Although there are a number of technologies to promote climate protection in companies (e.g., PlanA[16], Planetly[17] or CoZero[18]), we could not find any chatbots nor other innovative solutions to promote a "green office" in particular. While existing technologies allow for analyses of a company's CO_2 emissions based on data, the promotion of employees' behavioral change is not sufficiently covered so far. When expanding our search from innovative technologies to common mobile apps, we found existing services (Changers[19] and Stadtradeln[20]), who offer activity tracking and contest design functionalities. Although the app store ratings for the mentioned apps contain some user reservations, we were inspired by those apps when brainstorming gamification and tracking functionalities for our chatbot prototype. Nevertheless, the two existing offerings are either limited in their scope of support for climate-friendly activities or do not focus solely on environmental protection, so that the app's content depends significantly on the individual company manager and his or her expertise. We therefore consider KlimaKarl to be a valuable contribution to closing the market gap for the promotion of the "green office".

Third, we gathered additional requirements in a workshop at a multinational consulting company. In total, three employees and two project initiators participated. All employees held the position of a "consultant". The company representatives were selected for the workshop because they were members of a "sustainability task group". This group's major aim is to develop measures for integrating climate protection and sustainability efforts within the corporate strategy. In a five-hour-workshop, the participants first brainstormed new ideas on functionalities that were not covered by our initial collection yet. The attendees then jointly ranked the ideas in terms of their perceived value for users.

Fourth, we conducted a survey at Breminale, a German city fair. In total, 98 office employees were asked about their personal requirements on a prototype to foster climate-friendly behavior in an office setting. We chose the city festival—which took place in July 2019 in a large German city—for the survey, because it usually attracts a very heterogeneous group of people. The respondents were randomly selected and

[16] https://www.plana.earth
[17] https://www.planetly.org
[18] https://www.cozero.io
[19] https://www.changers.com
[20] https://www.stadtradeln.de

proactively approached by three volunteers in a personal manner. The volunteers checked with chosen individuals whether they worked in an office environment. If so, they were explained the KlimaKarl project and requested to fill out an online questionnaire that could be accessed via their private mobile phones (by help of QR codes) or via provided iPads.

For realizing a first version of the chatbot KlimaKarl, the collected requirements were condensed and prioritized in three steps. First, the project initiators and a developer performed an initial resource estimate for each functionality. Second, they rated the functionalities according to their potential "value" and development effort to come to a distinction between "must-have" and "nice-to-have" functionalities. Finally, the resulting ranking of functionalities was rechecked with the workshop attendees at the consulting company in a video call once again. Lastly, we came up with a manageable set of 20 design requirements (must-have), which were classified according to the categories "principal functionalities", "enterprise dashboard", "team dashboard", "user dashboard" and "user management & backend system". Table 7 lists and shortly explains the requirements.

Table 7. Requirements

Design Requirements (DR)	Description
Principal functionalities	
DR 1: Push-notifications with daily information about climate protection topics	Users receive notifications on background information and interesting facts regarding climate protection topics. They have the opportunity to rate the relevance of each notification from their personal point of view by help of a star rating-scale.
DR 2: Chat function to document completed tasks related to green office behavior	A chat function is realized, which allows to mark completed tasks (e.g., vegetarian lunch, turning off lights, using public transportation) by help of buttons in the categories of nutrition, energy and mobility. Each button is associated with certain credit points regarding CO_2 savings.
DR 3: Calculation of the kilometer distance of a route	The chatbot queries how users have covered a distance, e.g., by bike or train. If desired, the chatbot calculates the number of kilometers of the distance automatically in case the user enters a start and end address.
DR 4: Continuous feedback to scores	The chatbot reacts with the total number of points scored and with mimic art to give user feedback. Hence, employees are motivated to continue their environmental-friendly behavior.
DR 5: Instructions for team challenges	Employees (and teams) are provided with “green” challenges. When they complete a challenge, employee teams trigger a green donation from the employer, such as the compensation of distance kilometers or the planting of a tree.
DR 6: Employee surveys	The chatbot gives employees the opportunity to submit their own ideas for more climate protection in the company in a weekly survey. For this purpose, an

	additional button appears in the chat, which leads to a freeform text entry.
DR 7: Quizzes	The chatbot conducts a weekly quiz with employees, through which they can earn additional points.
Enterprise dashboard	
DR 8: Total ranking of all participating teams and their current positioning	Employees form teams and the scores of each single employee are aggregated. In a dashboard, the ranking of each team is shown.
DR 9: Donations for "green projects"	The total amount of money, which was triggered by all employees and donated by the company for green projects is listed.
Team dashboard	
DR 10: Individual ranking	The ranking of each individual employee within each team is provided.
DR 11: Progress indicator for the team challenges	Each employee team can perform team challenges, which require a particular score of points per category, e.g., nutrition or mobility (see DR 2). The progress of a team's task fulfillment is indicated by the chatbot.
User dash board	
DR 12: Badges	Every employee can collect badges. To receive these badges, they must have completed certain green tasks several times in a row. The more difficult the badge is to reach the more extra points are generated.
DR 13: Personal statistics	Each employee receives an overview of personal statistics, e.g., a weekly overview of the points achieved daily, the amount of CO_2 emissions avoided and points achieved per category.
User management & backend system	
DR 14: FAQ-section	A section with answers to frequently asked questions (FAQs) is provided.

DR 15: Support for finding teams	The chatbot helps to form teams by proposing users that are still in search for a team.
DR 16: User data management	The user can modify her/his master data (e.g., nickname, name, password) any time.
DR 17: Backend system	The backend system allows to modify the provided content, the chatbot's layout or granted scores amongst others.
DR 18: Transition design	The chatbot follows the transition design guidelines (cf. Liedtke et al. 2020) to promote sustainable design.
DR 19: Branding	The backend system allows to brand the mobile app with the company logo on the loading and setting screens.
DR 20: Statistics	The backend system allows to download the free text entries from the surveys, the rating of the tips based on the stars and an anonymous overview of the recorded green activities as CSV file.

4.3.4 Design and Development

The component diagram in Figure 13 provides an overview of the prototype's general architecture, which was developed to be executable via the operating systems iOS and Android. For that purpose, we used the Google Flutter[21] framework for implementing the frontend and the Express[22] framework for the backend. Thereby, we applied the programming languages Dart[23] and TypeScript[24] and we built on the integrated development environments Xcode, Android Studio and Visual Studio Code. More, the bcrypt[25] solution was used to create the login functionality. The communication between the front- and backend—but also the internal communication within these "blocks" (front-/backend)—was realized by help of REST (Representational State

[21] https://flutter.dev/
[22] https://expressjs.com/de/
[23] https://dart.dev
[24] https://www.typescriptlang.org
[25] https://www.npmjs.com/package/bcrypt

Transfers) APIs and the standards HTTP and JSON. In addition, MongoDB[26] was drawn upon to establish the database and the database management system.

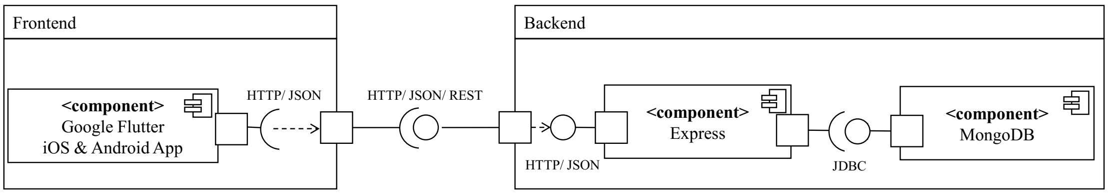


Figure 13. Principal architecture of the app.

A first design of the user interface, that matched with the design requirements, was discussed and revised by the development team using wireframes. Figure 14 shows a corresponding sketch of the tentative wireframes, which built the baseline for a more fine-granular design produced via the Adobe XD Design Kit[27]. In the course of the design implementation, templates of Google Material Design[28] and icons of “Evil Icons[29] were used. As an external service, the Google Distance Matrix API[30] was referenced to realize the calculation of distances in kilometers (see DR 3).

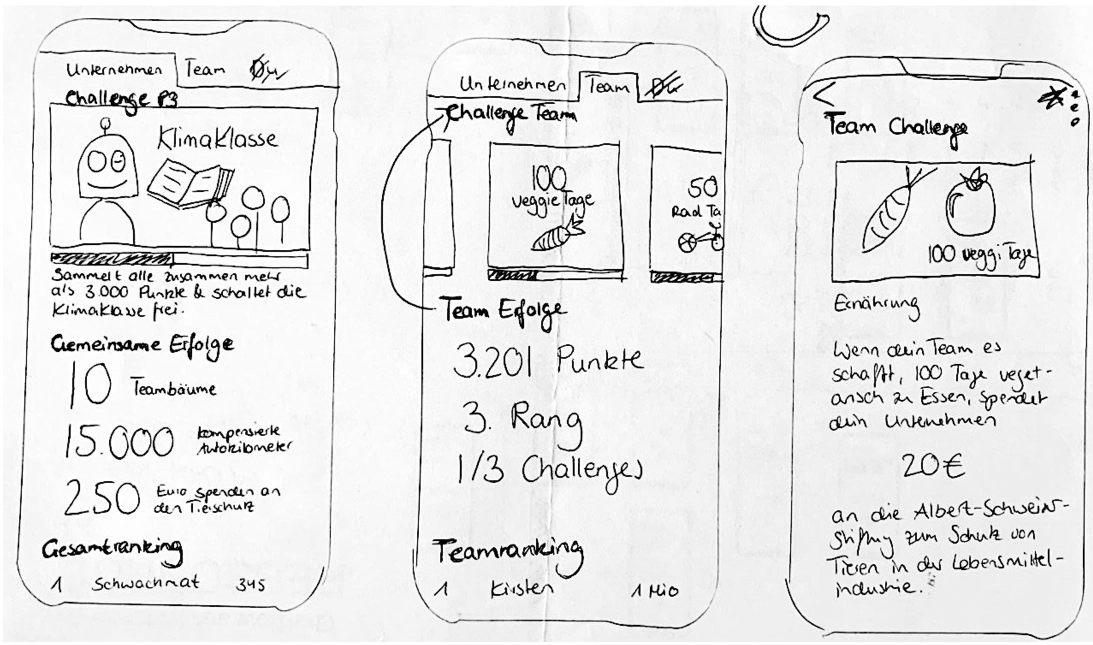
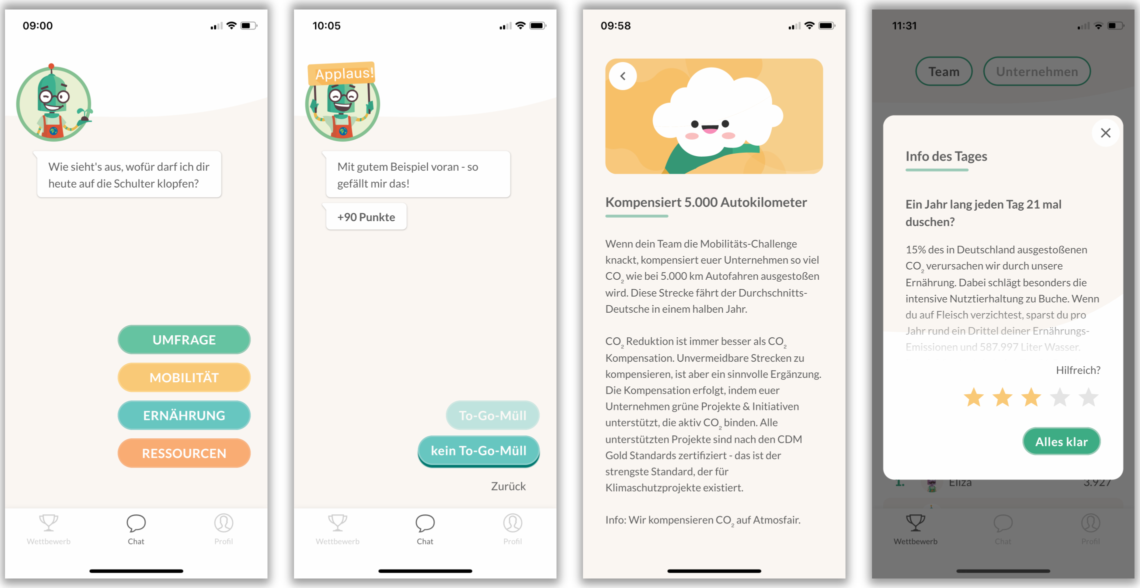


Figure 14. Initial wireframes of the app.

[26] https://www.mongodb.com
[27] https://www.adobe.com/de/products/xd/ui-design-kits.html
[28] https://material.io
[29] https://evil-icons.io
[30] https://developers.google.com/maps/documentation/distance-matrix/start

In regard to the implemented prototype, Figure 15 shows eight selected design examples of principal functionalities:

(1) The start screen of the chat to enter completed tasks (DR 2). The tasks are divided into the categories “mobility”, “nutrition” and “resources”. The green button represents the special task of the day such as a quiz or employee survey (DR 6, DR 7).
(2) The feedback on the credit points the user receives for a completed task. The feedback is supported by entertaining text messages and mimic art (DR 4).
(3) Instructions for a team challenge. In this example, the CO_2 emission of kilometers travelled by car is compensated once the team passes a certain point threshold in the mobility category (DR 5).
(4) Push-Notifications about climate topics and background information (DR 1).
(5) A team ranking (DR 8) based on credit points scored.
(6) An individual employee ranking (DR 10). Above the ranking it is further shown how many points are still missing to trigger a donation per category (DR 5).
(7) A user dashboard with Badges (DR 12) and
(8) personal statistics (DR 13).

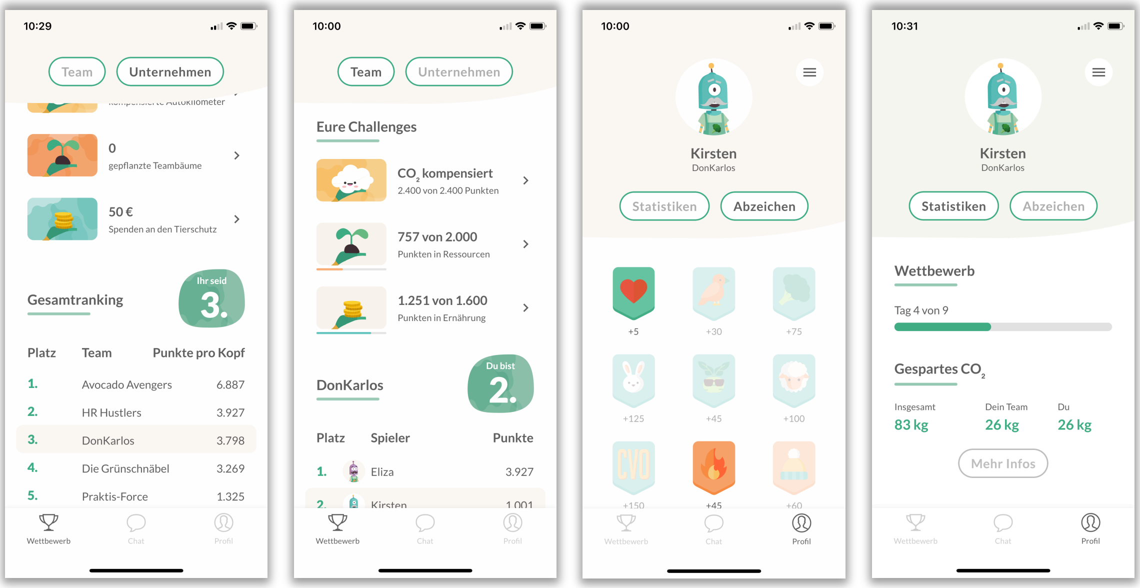


(1) Start-screen for documenting actions

(2) Feedback by text and mimic art

(3) Instruction for a team challenge

(4) Daily push-notification on climate topics



(5) Team ranking

(6) Individual employee ranking

(7) Badges

(8) Personal statistics

Figure 10. Screenshots of the app.

4.3.6 Demonstration and a First Evaluation

For demonstration and evaluation purposes, we field-tested the KlimaKarl prototype in September 2020 in cooperation with two companies and 74 voluntary office employees to investigate, whether the artifact is practicable in an entrepreneurial context.

One company is state-financed, provides advice on energy efficiency in a German federal state and recruited 21 participants to take part in our field test. Another company is globally operating in the retail sector and recruited 53 participants at its German headquarters. The chatbot was tested as part of a CO_2 saving competition with the following procedure. In week 1, the company representatives sent the logo, the donation budget to promote completed team challenges as well as mail addresses, user and team names to the KlimaKarl team. They loaded the logo into the designated app placeholder and set up all participants and teams in the backend so that mails were automatically sent with a randomly generated password with which the participants could log in. In week 2, all employees received two newsletters, one with information about the usage of KlimaKarl and the rules of the CO_2 saving contest as well as a reminder for the start date of the contest. In week 3 and 4, the employees took part in the KlimaKarl contest. As part of the contest (1) employees entered completed tasks via buttons in the chat and received feedback on the points achieved, (2) they took part twice in an employee survey, (3) they received and rated the daily tips with stars, (4) they could achieve team challenges and thus trigger various donations, (5) they could unlock badges for repeated tasks and (6) they had an overview of their ranking and statistics in the company, team and user dashboard. In week 4, the winning team was announced by releasing the ranking and a newsletter to all participants.

From a technical point of view, the test of the prototype worked well, except for a few minor details. Two participants stated that the chatbot was not accessible on one day. One participant did not receive any push notifications, although he declared to have activated them. From a content perspective, the field test revealed potentials for improvement, particularly considering the documentation of completed tasks. The rankings, tips, badges and some other features were praised. However, the participants wished for more variety in the dialogue with KlimaKarl. A concrete suggestion was to add more tasks or days on which tasks count double points.

Besides the general demonstration of the prototype’s practicability, we further wanted to test its usability to generate insights, whether the participating employees would behave in a more climate-friendly way during and after the chatbot-based contest. Therefore, the employees taking part in the field-test were asked to participate in an online survey (see Appendix C). The survey was created with Google Forms. Of the

74 employees, 25 filled out the questionnaire, which corresponds to a response rate of 28%. For the questionnaire, we used the System Usability Scale (SUS) by Brooke (1996) on a five-point Likert-scale. The SUS consists of 10 question items and is a recognized and widely used tool to easily query users' subjective perception of usability. An empirical evaluation of the scale shows that it is highly robust and versatile (Bangor et al. 2008). For this survey, we used the German version of the SUS according to Rummel et al. (2013), which has been developed in a crowdsourcing translation project with SAP usability professionals. We changed the term "system" to "app" for our survey. Figure 17 shows the SUS results as a box plot. The 25 participants rated the usability of the prototype with an average score of 3.89 with a standard deviation of 0.56 (maximum score: 5; minimum score: 1). Thus, the app was rated as rather easy to handle and user-friendly, but still leaves room for improvement.

To test whether the participating employees behaved in a more climate-friendly way while using the prototype, we asked them to indicate whether they performed a certain set of climate-friendly tasks (e.g., vegan lunch, taking a bike to work, turning off lights, etc.) more frequently than before the contest. Figure 16 summarizes the results in form of a histogram with absolute numbers. Accordingly, 18 of 25 respondents (72%) have eaten vegan or vegetarian food more often during the use of KlimaKarl than before. Between 6 and 10 respondents walked or cycled to the office, used the stairs instead of the elevator, switched off devices and lights before leaving work, and discussed climate protection topics with their colleagues more frequently. Contrary, heating habits and the use of public transportation did not change significantly.

To check whether employees have an intention to behave climate-friendlier in future, we used question items of the expanded Theory of planned Behavior by Perugini and Bagozzi (2001) with a five-point Likert-scale. Of the different constructs we only used those items suitable to measure the "desire" and "intention" to behave in a more climate-friendly way after completing chatbot-based contest. The German translation of the items was done with the help of a forward/backward translation with two PhD students. Figure 17 shows the survey results as box plots. The 25 respondents rated their desire to behave in a more climate-friendly way after using KlimaKarl as an average of 3.5 with a standard deviation of 0.88 (maximum score: 5; minimum score: 1). Their concrete intention to do so was rated as an average of 3.3 with a standard deviation of 1.23 (maximum score: 5; minimum score: 1). Hence, the results of the first evaluation indicate the chatbot's potential to increase employees' climate-friendly behavior.

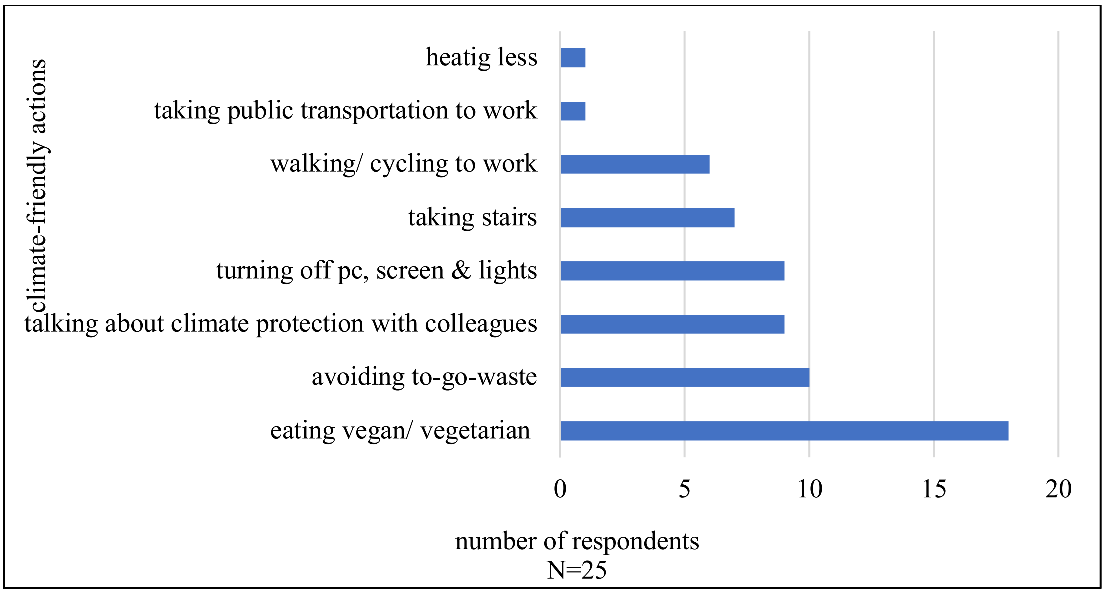


Figure 16. Climate-friendly activities performed more often while using the prototype.

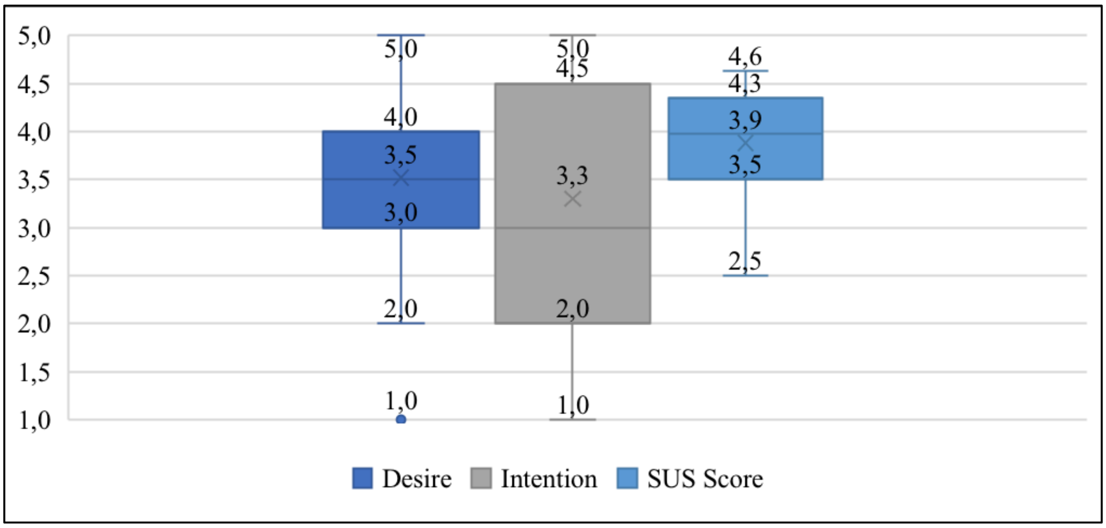


Figure 17. SUS score, desire & intention to act in an climate-friendlier way after having used the prototype.

4.3.7 Discussion and Benefits

Although chatbots have received increasing attention in literature recently, their use in the course of entrepreneurial environmental sustainability efforts is not in the center of current research yet. Considering that climate protection is one of the most important challenges of our time, the KlimaKarl prototype aims to address this research gap and to trigger a discussion of how chatbots can promote climate protection. Thereby, a review of existing apps and chatbots on the German market shows that—from a general perspective—companies are already using digital technologies in a business and office context. However, they do not yet sufficiently do so to promote their CSR. In a field study with 74 office employees at two companies the prototype proved as applicable from a technical side, with minor exceptions regarding its accessibility and the availability of push notifications. We used the SUS to measure the usability (Brooke 1996). The 27 people who took part in the online survey rated the chatbot's usability with an average of 3.89 on a scale of 1 to 5. Although the entertainment factor of the chat dialogue could be increased according to the feedback, this score is satisfactory for a first shot of the prototype.

Two further aspects of the online survey provide an initial assessment of the chatbot's potential for triggering behavioral change both during and after using the prototype. Participants indicated which climate-friendly activities they performed more often whilst using the prototype than before. Two-third of the respondents were more likely to perform a vegan or vegetarian diet, and other activities such as turning off lights and cycling to work. Thus, the participants stated to have actually changed their behavior. In order to obtain initial indications as to whether this change is likely to be permanent, the desire and intention for future behavior were assessed using selected items of the expanded Theory of Planned Behavior (Perugini and Bagozzi 2001). Both scores are in the upper middle range and indicate the possibility of a permanent change in behavior.

However, this first evaluation of the KlimaKarl prototype has limitations. First, only employees of two particular companies participated. Since corporate cultures and strategies about sustainability can differ considerably, additional study participants from more companies have to be recruited in future evaluation steps. More, since the respondents filled out the online survey voluntarily, a self-selection could probably be given. Furthermore, future evaluation measures for behavioral change should be based on revealed rather than self-reported behavior, e.g., by means of experiments. However, at this stage of the chatbot development, the goal was not to precisely quantify the desired effects, but to find out whether KlimaKarl has the potential to influence employees' behavior or not.

The contribution of this research for practice is twofold. First, managers will receive a running chatbot solution to motivate their employees for green office behavior and integrate climate protection into the company culture. Therefore, means to support running CSR efforts are given. The chatbot may also be provided by non-profit organizations in order to reach broader parts of society beyond specific companies. Second, the use case of KlimaKarl may provide inspiration for managers to examine the appropriateness of other digital technologies to promote climate protection within an enterprise (e.g., big data analytics). Regarding research, we contribute to the lively discussion of how chatbots may be purposefully used for internal purposes (e.g., Meyer von Wolff et al. 2019). In this respect, we introduce "green office behavior" as a further application field, that may profit from the chatbot technology. Additionally, we provide an overview of requirements a corresponding chatbot solution should meet to promote climate-friendly behavior of employees. Finally, the results from the evaluation conducted so far may trigger further investigations in the IS community to analyze the sustainability of changes in employee behavior by help of digital technologies. Further research could also analyze the impact of including employees in the CSR strategy—by help of digital technologies—on the success of a company's sustainability activities (e.g., a better image among stakeholders).

However, despite the potentials associated with chatbots (e.g., Dale 2016), it needs to be mentioned that some challenges may prevent users from interacting with this technology. According to a recent study, which was conducted in the United States with more than 1.000 participants (cf. Drift 2018), a considerable amount of users prefers to interact with humans instead of chatbots, has concerns about error-prone working procedures or rejects chatbots that are integrated with social networks. Another challenge is that designing chatbots that are able to react to unforeseen situations is considered as complex in literature (e.g., Augello et al. 2017) just as enabling human-like conversations by help of suitable NLP mechanisms (Klopfenstein et al. 2017).

4.3.8 Conclusion and Outlook

In the paper at hand, we develop a chatbot prototype, KlimaKarl, that promotes climate-friendly behavior of employees within companies. The results from the demonstration and first evaluation are encouraging. We could show that our prototype is of rather high usability and may motivate people to behave in a more climate-friendly way. Though, as mentioned, further evaluations at companies from different branches have to be done. More, the completeness of requirements cannot be guaranteed, while alternative architectures for the app could be thought of. In future steps, we plan to extend the chatbot's functionalities, e.g., by the possibility to ask open questions or the access to past daily tips.

In the next steps, we will further evaluate the app in order to maximize the chatbot's environmental impact. After a corresponding revision, we intend to make the chatbot available to German companies in autumn 2021. Depending on how KlimaKarl will be accepted in practice, we would be happy to translate the app to other languages and to launch in on an international level.

Chapter 5

Discussion

5 Discussion

The standard of living, everyday life and well-being of society changed over the last three centuries in the face of technological progress. The socio-economic implications of new technologies have always been ambivalent, but they have never developed as rapidly or been as far-reaching as today's. Pursuing the vision of Society 5.0, this dissertation aimed to contribute to the resolution of this ambivalence by shedding light on the mobilization of citizen data to increase social welfare. To this end, it focused on the active participation of civil society as a promising approach to increasing data availability and quality. As the heart of this dissertation, the studies presented in chapter 4 took an interdisciplinary approach to provide diverse perspectives on drivers, barriers, and technologies for sharing and generating personal data.

Contributions to research. The experimental papers give empirical insights on how and why individuals are willing to share their personal data for Society 5.0. A core characteristic of our data-driven economy is that sharing personal data usually implies a risk of privacy violation. The results show, however, that despite this risk, civil society is still inclined to share their data to increase social welfare. While this willingness is only slight, it is stable across various factors.

First, across different types of data. People are inclined to share both singular types of data such as their current location, as well as extensive private intent data that can usually only be collected by private industry. These data even include sensitive information such as banking data, social media data, browsing history, and health information. Second, across different contexts: there is both a willingness to upload data to a database to operate a smart assistant to foster socially preferable behavior change, and to share data for monitoring and statistical analysis in the context of a pandemic. Third, across different cultures, specifically the US and German civil societies. Fourth, across different domains of social welfare: although a direct comparison showed slight differences in promoting a sustainable environment and a sustainable health system, willingness to share data was consistently present in both domains, as well as in promoting public health in a pandemic. The empirical results also reveal knowledge on which circumstances favor the willingness to share data voluntarily for the benefit of society. These include a low privacy risk, a high perceived moral obligation, that data will not be managed by private industry, and trust in the recipient of the data, e.g. in the case of the state.

The existing information systems literature typically considers the decision to disclose data under privacy risk as an exchange of goods. Data are exchanged for a particular service and risks are accepted for certain benefits and rewards. In parallel, the literature on altruism finds that people often are willing to engage in self-sacrificing behaviors and perform charitable donations. This is also true in the literature referring to the donation of data types such as research and health data. The empirical results of this dissertation are consistent with this literature and contribute to its extension in three ways.

First, they take into account an essential aspect that has been neglected so far: data from a single person is not sufficient. In order to improve the quality of data, avoid biases and operate innovative technologies, a sufficient number of people must be willing to disclose their data. Therefore, individuals make the decision to share data not only under privacy risk, but also with an uncertain payoff. They are unaware of whether enough fellow citizens will share their data so that, for example, the operation of a technology or the control of a crisis will actually be achieved. Since this uncertainty is a barrier to cooperation, the stable willingness to share data in the results of this dissertation is even more striking.

Second, the existing literature has so far focused on the disclosure of small data sets or individual data types. While individual health data or survey responses also make a contribution, the contribution of large private intent data generated automatically with the help of digital tools is disproportionately larger. It was therefore not self-evident, but an additional insight, that civil society would also be willing to share their large, diverse and timely private intent data.

Third, both online experiments were conducted at a time when the power of civic data to enhance society's well-being has arguably never been more explicit and tangible. During the corona pandemic in 2020, the discussion around the potentials and risks of using personal data for the benefit of society received significant media attention and reached broad parts of general society. There is a contribution in replicating previous research on data sharing at this particular time, when both the understanding of data's potential for social welfare, as well as the risks associated with it, appear to have increased.

The DSR paper builds on the context of Paper I and adds a more technical perspective. The empirical results of the online experiment revealed that people are willing to provide their data to a database that enables the operation of a smart assistant. In close cooperation with civil society and practitioners, Paper III developed a detailed concept of how a corresponding smart assistant can actually be implemented using chatbot technology. A chatbot requires the participation of civil society in two respects. First, it requires large amounts of data to train natural language understanding and to develop effective strategies to motivate behavior change. Thus, individuals need to contribute private intent data to the development of the chatbot, but do not necessarily have to use the chatbot. Second, the smart assistant allows its actual user to record their behavioral data and applies developed strategies to motivate behavior change. Thus, users do not need to contribute large private intent data, but can use the chatbot to generate new public intent data. The chatbot thus can serve as a digital tool that enables the mobilization of CGD. The paper focuses on the second type of civil participation and includes the development of a prototype as part of an actual mobile app. The strategies to motivate behavior change are static for now, but can be made data-driven and dynamic in future steps. Early tests in practice have shown that users not only document their behavioral data, but also show initial tendencies to change their behavior in a socially preferable way.

Literature on CGD is still emerging and includes in particular the derivation of its relevance based on current challenges, its potentials and actual case studies. However it needs to be complemented by non-profit digital tools that allow citizens to generate new datasets. To date, CGD initiatives have been launched particularly by governments and non-profit organizations, partly with support of academia. For these specific projects, appropriate technology has been provided or was available opensource, such as the OpenWorld Map. While technology is supposed to be as diverse as the data it is meant to generate, the scope of existing public technologies is still limited. Their extension particularly requires non-profit and opensource developments from academic, non-profit and governmental organizations, so that citizens do not have to rely on services from private industry and risk privacy violations. While current information systems research shows considerable effort devoted to the development of corresponding technology, results cannot yet cover the wide range of demands. This dissertation contributes to existing results with the technical development of the chatbot prototype. Not only have chatbots received little recognition as a CGD tool, but the proposed chatbot can proactively be used by broader civilian society independent of local and occasional CGD initiatives. While the paper develops the chatbot exemplary for an office workforce in particular, the technological approach can guide and easily be adapted by social welfare-oriented organizations. The potential use of the chatbot as part of a competition within companies can further generate behavioral data in a business environment. These could contribute to the effective design of CSR activities and thus additionally unfold socially desirable effects as part of corporate efforts.

Implications for Practice and Politics. This dissertation provides empirical evidence that citizens are willing to share their personal data for social welfare, even when facing privacy risks and uncertain payoffs. These results are promising. However, in order to actually unleash the potential of civic participation, the data sharing must be executed technically. The crucial conversion of the general willingness to share data to the actual transfer of data raises the central question of an appropriate, politically organized infrastructure. How can data governance be designed consistently across nations in order to respect the civic ownership and guarantee data quality by including all parts of society and regions?

In November 2020, the EU proposed answers to this question as part of the new Data Governance Act (European Commission 2020b). The aim of this act is “to foster the availability of data for use by increasing trust in data intermediaries and by strengthening data-sharing mechanisms across the EU” (European Commission 2020b, para. 1). In the past, other regulations have already been passed to create a European data strategy, including the GDPR on the protection of personal data (European Commission 2016) and the Open Data Directive on the reuse of public intent data (European Commission 2019). The Data Governance Act builds on these by proposing a framework to harmonize existing national data sharing practices, taking into account established European rules. In light of this dissertation's findings, the act is particularly relevant in that it encompasses, beyond existing regulations, the sharing of private intent data across organizations and the management of individuals' personal data for altruistic purposes (European Commission 2020b).

On the one hand, the Data Governance Act is partly in line with the findings of this dissertation and sets the course for an appropriate infrastructure. For example, the EU introduces a distinct registration process for organizations in order to qualify as recipients and managers of data donations. By committing to abide by certain rules in handling the personal data provided, these organizations will receive certification as a "Data Altruism Organization recognized in the EU" (European Commission 2020b, section 3, para. 4) and thus as a trusted intermediary. Considering the empirical results, such designated process can foster individual willingness to share personal data in two ways. First, because individuals are more willing to share their data with organizations if they consider them trustworthy and believe that they will actually use the data for social welfare. Second, because disclosing data to a certified intermediary involves a lower privacy risk, thereby favoring voluntary sharing.

On the other hand, the Data Governance Act is insufficient in important aspects given the outlined ethical dangers of a data-driven society. The theoretical and empirical results of this dissertation provide practical and political implications as to which aspects of the act should be further revised in favor of a Society 5.0.

Incomplete or low-quality data are roots of inequality and discrimination. This dissertation presented civic participation in data governance as a promising approach to fill gaps and improve data quality. By initiating new data generation or sharing existing data with social-welfare oriented organizations, citizens can actively shape data-based technologies and decisions. The Data Governance Act addresses in various sections the facilitation of data altruism, which is considered as "data voluntarily made available by individuals or companies for the common good" (European Commission 2020b, section 5, para. 2). The general addressment is a positive advancement and, in this form, an extension of previous regulations. While the act generally acknowledges the idea of data altruism and claims its encouragement, it neither adequately covers the specific technical implementation details nor solutions to significant ethical issues of a cross-border infrastructure.

Like the literature this dissertation built on, the Data Governance Act considers data sharing for altruistic reasons as a form of donation without personal rewards but with social utility. Although donated data might be shared by data intermediaries across all members of the EU, the draft does not articulate how exactly the pay-off structure can be designed in an equitable and fair manner. There is no indication on how to ensure that the utility affects societies of all members equally, and whether this would even be an aspiration. Yet this issue is pressing as data donations are unlikely to make equal contribution across member states for two reasons. First, because, as in conventional political operations, conflicts of interest can arise. Typically, powerful and richer nations are better able to assert their interests and protect their access to resources, including data. Second, because not all members have the same technical capabilities. A negative scenario may be that the voluntarily donated behavioral data of people from less technologically developed countries is used in particular by better developed countries to train and operate innovative technologies. In this case, the welfare of technically advanced societies in particular would be promoted and inequality would further increase. The Data Governance Act should therefore formulate specific requirements for the pay-off structure of voluntary data donations and communicate these transparently to civil society. Empirical results show that individuals do not always distinguish between different levels of impact of their data on social welfare. Whether their data has an impact at all is, however, indeed a decisive factor in altruistic data sharing decisions.

There are further deficits in the actual implementation of data donations. In chapter 3.2.1, this dissertation considers the use of user-centric data management models as a feasible approach to managing the distribution of private intent data. Regulators need to propose a comparable approach that would technically enable the distribution of data in a manner that respects the individuals' ownership and ensures a safe and secure data transfer. While a certification of intermediaries is positive in itself, user-centric management models, e.g. based on blockchain, could render their operation obsolete by putting the individual in the center of control.

Further, the Data Governance Act should be supplemented by proposals as to how all citizens can obtain their right to share data. After all, not everyone has equal access to a digital infrastructure. If especially privileged citizens share their data, the fundamental problem of disproportionate and biased data and the resulting unequal treatment of social groups will not be solved, but intensified. While the access to digital infrastructure is a general challenge involved in civic data sharing and CGD, designated initiatives such as the Data Governance Act ought to take it into account.

This dissertation further holds empirical evidence that civil society's willingness to share data can change in extreme situations, e.g. while fearing for health in a pandemic. In order to avoid ethically questionable timing of data sharing measures and to transparently educate civil society about the relevance and risks of their data sharing, data government efforts should further be complemented by advisory services and communication guidelines. These can prevent one-sided reporting or solo efforts by individual nations to generate unnecessary or disproportionate data, e.g., in support of surveillance measures. Education on data sharing as part of communication campaigns and a resulting dialog in civil society could lead to the positive side effect of encouraging a willingness to share data for social welfare. According to the results, willingness to share data depends largely on the extent to which people expect others to do so.

In order to shape technical progress in line with a Society 5.0, the potential of data will have to be mobilized primarily to increase social welfare. A healthy economy is an important means to this end. The Europe-wide draft of a corresponding data governance would have had the scope and strength to lay the foundation stones. However, it currently prioritizes the market and the economy and only secondarily and insufficiently considers various technical and social challenges of data altruism (see also Vrikki 2021).

To unlock its full potential and scope, mobilizing civic data should not be a bureaucratic act, but part of the daily life of citizens. The derivation of this dissertations insights' practical and political implications along the Data Government Act obviously takes particular note of European efforts to this end. Yet this deliberately chosen perspective is considered justified because the EU, with attempts such as the GDPR, is one of the world's early movers in the socially oriented use of data (e.g., Schwartz 2019). Beyond the EU, of course, there are other, international efforts to mobilize data for social welfare.

A leading role in implementing the technical infrastructure—both for sharing existing data and for generating new citizen data—is played by social-welfare oriented organizations and initiatives. These include, for example, the Global Partnership for Sustainable Development Data[31]. The network promotes collaboration between governments, private industry, and civil society to use data for measuring and achieving the SDGs. How individuals can share data, however, tends to be neglected. The World Bank focuses on the individual while piloting an innovative approach called the Health Data Bank.[32] Using the app, civil society can collect all their online health data in this Health Data Bank and manage, share and even monetize it in a user-centric management system. Data collaboratives from NYU GovLab and UNICEF[33], further provide a platform for private industry in particular to share data with the purpose of enriching public intent data.

There are more and more initiatives and practical approaches of this kind which is positive and promising. Nevertheless, these approaches are still uncoordinated and only rarely actively involve the individual citizen—and if they do, then rather specific groups and not the general society.

[31] https://www.data4sdgs.org
[32] https://www.healthbank.coop
[33] https://www.thegovlab.org

Chapter 6

Conclusion

6 Conclusion

The research of this dissertation indicates that civil society is generally open to active participation in data governance and that innovative technologies such as chatbots can support them in generating new data. Conducting online experiments with different societies, there is empirical evidence that individuals are willing to share their data in the spirit of Society 5.0 and that this willingness depends on the privacy risk, the trustworthiness of the data recipient, moral obligation and fear, among others. These results especially contribute to the existing literature by recognizing that a sufficient number of individuals must disclose their data to generate a positive effect on social welfare and by considering up-to-date contexts and technologies.

We currently lack a coherent and organized and large-scale approach to unlock citizens' willingness to share data. We need to find new ways to make data sharing for social welfare an integral part of our daily lives just as sharing data with private industry for commercial purposes is. The current corona pandemic has highlighted the vast potential of civic data to increase social welfare by protecting public health. However, it has also highlighted the inadequate preparation in mobilizing such data. In many nations, the technical infrastructure, such as apps that ensure privacy, first had to be conceptualized and developed in order to actually enable the collection of the corresponding data. These planning and technical implementations tended to be dencentralized, uncooperative, and lacked uniform European guidelines, costing valuable time. Other, mostly low-income countries, still do not benefit from the corresponding technologies and are left without the support of data in the fight against the virus. Increasing crises due to climate change, for example, will only boost the importance of data in the future. We should take advantage of the available knowledge about data, innovative technologies and associated challenges today in order to include all parts of society and be better prepared in the future.

Taking into account some limitations, this dissertation contributes to knowledge on how the civic participation can increase public intent data quality and thereby foster a Society 5.0. Yet the results can only count as a few pieces of the puzzle. Many questions, such as the accountability of algorithms, the protection of privacy, the reduction of inequality and the response to monopolization, remain not unanswered conclusively. In order to assemble the big picture, we now need a joint effort by academia, legislators, the private and non-profit sectors, and the civic society. If we manage to learn from the past three centuries, ask the right questions and set the right priorities for the future, we can shape technological progress in a way that resolves its ambiguity and favors the sustainable development of our world.

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Appendix

A Appendix to Chapter 4.1

A1 Data and Additional Analyses

Table A1.1. Comparison of Treatment Characteristics

Variable	Risk-treatment conditions			*p*-value for equality across conditions
	Low risk	Medium risk	High risk	
Age	39.919	37.487	37.136	.154
Education	4.848	4.826	4.932	.186
Gender (male = 1)	1.570	1.604	1.570	.425
Income	5.602	5.570	5.737	.322
Living standard	3.419	3.483	3.529	.087
Political views	3.312	3.377	3.397	.385
Religious views	3.234	3.309	3.386	.138
Expected behavior others	52.046	52.698	52.710	.870
Future time orientation	3.167	3.261	3.209	.106
Human-assistant trust	3.305	3.295	3.383	.135
Interpersonal trust	3.374	3.383	3.391	.959
Risk attitude	2.957	3.005	3.079	.148
Social value orientation	.474	.466	.469	.831
	Impact-treatment conditions			*p*-value for equality across conditions
	Low impact	Medium impact	High impact	
Age	37.435	36.973	40.185	.087
Education	4.824	4.940	4.839	.122
Gender (male = 1)	1.589	1.608	1.544	.095
Income	5.661	5.667	5.582	.732
Living standard	3.467	3.478	3.487	.926
Political views	3.317	3.357	3.411	.347
Religious views	3.272	3.354	3.302	.559
Expected behavior others	54.164	52.514	50.764	.062
Future time orientation	3.238	3.197	3.201	.587
Human-assistant trust	3.301	3.335	3.347	.615
Interpersonal trust	3.344	3.405	3.397	.560
Risk attitude	2.979	3.046	3.014	.574
Social value orientation	.473	.460	.476	.390

Note: The far-right column reports *p*-values of ANOVA *F*-tests from the respective three treatment conditions.

Table A1.2. Comparison of Domains Characteristics

Variable	Domains of social welfare		*p*-value for equality across domains
	Sustainable environment	Sustainable health system	
Age	37.640	38.736	.392
Education	4.835	4.903	.175
Gender (male = 1)	1.583	1.579	.870
Income	5.534	5.744	.031
Living standard	3.424	3.532	.008
Political views	3.328	3.396	.199
Religious views	3.262	3.359	.124
Expected behavior others	52.321	52.651	.778
Future time orientation	3.203	3.220	.650
Human-assistant trust	3.348	3.306	.294
Interpersonal trust	3.376	3.389	.793
Risk attitude	3.017	3.010	.903
Social value orientation	.468	.471	.772

Note: The far-right column reports *p*-values of *t*-tests for mean difference across the two domains.

A1.3. Risk and Impact Level Differentiation

Perceived risk level per treatment condition	Sustainable environment	Sustainable health system
ANOVA equality across condition	.002	.006
Medium risk vs. low risk	.089	.087
High risk vs. low risk	.001	.005
High risk vs. medium risk	.362	.553
Perceived impact level per treatment condition		
ANOVA equality across condition	.437	.335
Medium impact vs. low impact	.970	.930
High impact vs. low impact	.450	.327
High impact vs. medium impact	.589	.523

Note. The table reports *p*-values of ANOVA *F*-tests and Tukey's method results for perceived level of risk and the perceived level of impact.

Table A1.4. Summary Statistics of Demographics

Domain	Mean	Std. Dev.	Min	Max
Age	37.428	1.139	18	75
Education	4.870	1.032	1	7
Gender (male=1)	.581	.504	1	3
Income	5.639	1.992	1	9
Living standard	3.476	.839	1	5
Political views	3.362	1.089	1	5
Religious views	3.310	1.293	1	5

Table A1.5. Summary Statistics of Beliefs and Attitudes

	Mean	Std. Dev.	Min	Max
Willingness to donate	54.314	30.303	0	100
Moral obligation	3.026	0.934	1	5
Expected behavior others	5.248	24.091	0	100
Future time orientation	3.212	0.749	1	5
Human-assistant trust	3.328	0.809	1	5
Interpersonal trust	3.383	1.040	1	5
Risk attitude	3.014	1.059	1	5
Social value orientation	.470	.211	-.3	1.1

Table A1.6. Correlation Matrix of Demographics, Beliefs, and Attitudes

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	Willingness to donate	1														
2	Moral obligation	.642	1													
3	Age	-.015	.004	1												
4	Education	.200	.173	.009	1											
5	Gender (male=1)	.105	.134	-.009	.074	1										
6	Income	.028	-.024	.047	.268	.009	1									
7	Living standard	.414	.418	.0296	.273	.068	.211	1								
8	Political views	.280	.342	.037	.068	.085	.034	.385	1							
9	Religious views	.283	.338	.016	.121	.023	.028	.362	.538	1						
10	Expected behavior others	.473	.412	.012	.077	.093	-.002	.336	.295	.299	1					
11	Future time orientation	.252	.362	.055	.099	.076	-.062	.273	.270	.252	.160	1				
12	Human-assistant trust	.622	.610	.005	.182	.120	.020	.477	.402	.394	.442	.319	1			
13	Interpersonal trust	.426	.415	.036	.215	.100	.031	.441	.331	.336	.336	.282	.513	1		
14	Risk attitude	.521	.596	-.002	.209	.197	.054	.561	.502	.467	.420	.400	.662	.521	1	
15	Social value orientation	.013	-.018	.037	-.049	-.019	-.063	-.041	-.127	-.069	-.017	-.038	-.026	.057	-.085	1

Table A1.7. Summary Statistics of Domain and Treatment-Specific Control Variables

	Mean	Std. Dev.	Min	Max
Benefits for the public	53.468	19.208	0	100
Benefits for each user	46.001	19.104	0	100
Pref. database for environment	3.345	1.131	1	5
Pref. database for health	3.381	1.091	1	5
Pref. sustainable environment	4.131	.852	1	5
Pref. sustainable health system	4.026	.908	1	5
Previous environmental behavior	3.612	.870	0	5
Previous health behavior	3.921	.749	0	5

Table A1.8. WDPD Comparison per Treatment Group

Risk-treatment groups	Overall	Sustainable environment	Sustainable health system
ANOVA equality across condition	.007	.037	.133
Medium risk vs low risk	.012	.033	.288
High risk vs low risk	.024	.193	.135
High risk vs medium risk	.960	.713	.915
Impact-treatment groups			
ANOVA equality across condition	.808	.442	.438
Medium impact vs low impact	.939	.697	.410
High impact vs low impact	.948	.415	.717
High impact vs medium impact	.791	.891	.889

Note: The table reports *p*-values of F-tests and Tukey's method results for *WDPD* means for level of risk and the level of impact.

Table A1.9. Comparison per Operating Organization

	Overall	Sustainable environment	Sustainable health system
P-value for equality across groups	.000	.000	.091
Government vs academia	.787	.248	.756
Private industry vs academia	.001	.013	.080
Private industry vs government	.000	.000	.321

Note: The table reports *p*-values of F-tests and Tukey's method results for *WDPD* means for managing organization.

Table A1.10. WDPD Comparison per Algorithm Type

	Overall	Sustainable environment	Sustainable health system
WDPD (self-learning) < WDPD (human-supervised)	.724	.920	.305
WDPD (self-learning) = WDPD (human-supervised)	.552	.159	.609
WDPD (self-learning) > WDPD (human-supervised)	.276	.080	.695

Note: The table reports *p*-values of *t*-tests for mean difference of *WDPD* across databases that are used to run a human-supervised and a self-learning smart assistant.

Table A1.11. WDPD and MO Comparison per Domain

Variable	Domains of social welfare			*P*-value for equality across two domains
	Overall	Sustainable environment	Sustainable health system	
Willingness to donate	54.314	55.100	37.136	.277
Moral obligation	3.026	3.064	2.987	.093

Note: The table reports *p*-values of *t*-tests for mean difference of *WDPD* and *MO* across domains.

Table A1.12. WDPD to Private Industry

	dv: *WDPD* to private industry	
	Coef.	*p*
Profit orientation of private industry	-3.332	.000
Skill of private industry	.972	.254
Trustworthiness of private industry	6.013	.000
Moral obligation	.553	.530
Risk	.801	.293
Impact	.464	.524
Age	.006	.686
Education	-.399	.552
Female	-2.320	.066
Income	.099	.768
Living standard	-1.470	.135
Political views	1.469	.061
Religious views	-.230	.729
Exp. behavior others	.039	.184
Future time orientation	.366	.698
Human-assistant-trust	-3.787	.004
Interpersonal trust	-.856	.290
Risk attitude	.086	.929
Social value orientation	-2.734	.339
Benefits for the public	.048	.793
Benefits for each user	-.027	.290
Constant	31.331	.007

Note: The table reports coefficients and *p*-values of an OLS regression analysis

A2 Online Experiment and Survey

A2.1 Introductory Text for Participants

Research

This study is part of a research project that investigates ways to help the public benefit from its personal data. The study is run by Professor Lars Hornuf and Kirsten Hillebrand from the University of Bremen. You will receive between $0.40 and $0.55 for taking part in this study, which can be completed in approx. 20 minutes. Your actual payment will depend on the choices you make during the study. On the next page, we start with a brief explanation of

- Why individuals need to grant access to their personal data to promote public welfare,
- how individuals can support the promotion of public welfare by providing their personal data, and
- the risks associated with providing personal data.

We then show you two scenarios, in which you can choose between uploading and not uploading your personal data to a database, so that these data can be used to promote the public good. You will answer questions about moral obligation and your willingness to provide data.

Consent

Your decision to complete this study is voluntary. Your answers will be collected and analyzed in an anonymous form, which means that you cannot be reidentified. Any data we process will be encrypted with a random session ID. We will neither collect your IP-address, name, location nor any other data that could identify you. Besides your answers, we will exclusively collect the following data: duration of participation, the survey page on which participation ended, browser, mobile device, date and time of access.

Because this study is conducted by a German university, the collected data will be transferred to and stored on university servers in Bremen, Germany. The anonymized data will be stored for 10 years and deleted afterwards. All data is collected via the service provider Unipark. Hence, the collected data will be additionally stored on servers of this service provider. Uniparks's server park is located in Frankfurt, Germany, BSI-certified and is subject to the security requirements of ISO 27001. To the best of our knowledge, Unipark will not collect any additional data to the one stated above and your anonymized data will be deleted from the Unipark servers as soon as the data collection is completed, i.e. the online survey is taken offline. The aggregated results of the research may be presented at scientific meetings, published in scientific journals or in other ways shared with the scientific community in an anonymized form. Clicking on the checkbox below indicates that you are at least 18 years of age and agree to complete this study voluntarily.

At the end of the study you will receive a unique survey completion code. You can then enter this code at MTurk in order for us to verify your participation and release your payment. During this process, we can observe but will not store your worker ID assigned by MTurk. We will not observe your name, banking details, or any other individual-related data.

Questions/Concerns

Please contact the researchers behind the study if you have any questions or concerns via Kihi@uni-bremen.de.

A2.2 Background Information on the General Topic

Personal data for public welfare

In the report "A World That Counts," the United Nations (UN) calls for the mobilization of data to promote public welfare. Data and new technologies have the potential to transform societies and to protect public goods such as a sustainable environment or health system. Thus, data can maximize individual and social welfare in the United States. Like the private industry or academia, US-American civil society is equally part of the global data ecosystem. Data-driven technologies such as smart assistants enable individuals to make choices that are good for them and the world in which they live. However, available data for such technologies need improving. As the UN report states, whole groups of people and important aspects of their lives are still not captured digitally. More diverse, integrated, and trustworthy data lead to better decision making and real-time citizen feedback. According to the UN, providing access to such data is essential to promote social welfare.

This study: smart assistants & privacy risks

In this study, we examine if individuals provide their data to improve data quality and decision making. We specifically focus on smart assistants, a data-driven tool that converts large amounts of data into personalized information**.** This information is available when and how the user wants it. A smart assistant could help users make more environmentally friendly daily choices and thus contribute to a sustainable environment—for example, by selecting relevant information according to consumption patterns and providing tips that are tailored to habits and easy to follow. (To demonstrate that you have carefully read the instruction, please do not tick the check box regarding your age below.) Although a smart assistant can promote eco-friendly choices, leading to a sustainable environment, it holds a privacy risk: providing your data to a smart assistant means risking the possibility that your data will be leaked. For example, your data could be hacked by a third party, you could be identified even though your data have been anonymized, or your data could be used for purposes other than what you agreed to.

Optional additional information

On the following pages, we present our best estimates on how the smart assistant might perform in helping users live environmentally friendlier everyday lives. The predictions are based on the following scientific studies:

- On behalf of the German Federal Environment Agency, U. B. A., Schächtele, K., & Hertle, H. The CO_2 Balance of the Citizen Research for an internet-based tool for creating personal CO_2 balances. (www.uba.co2-rechner.de)
- Klein, Daniel (2009, June 18). How many trees are needed to bind one ton of CO_2? Das Handelsblatt. Retrieved from www.handelsblatt.com.

A2.3 Part 2a of the Experiment

Presentation of the Scenario and Trade-off to Participants (Exemplary for Domain 1 with low Risk and high Impact)

Scenario 1

Imagine a smart assistant that supports US users in living environmentally friendlier everyday lives, thereby promoting a sustainable environment. Every English-speaking person with a smartphone in the United States could use the smart assistant.

However, to develop and operate an assistant that offers informed and comprehensive decision support on sustainable behavior, there must be access to a sufficiently large database of diverse and trustworthy data. The database requires the following data sets in an anonymized form:

- Basic personal information such as age, gender, level of education, and job and contact information;
- personal purchase lists and payment information;
- personal medical records and information;
- personal posts and likes on social networking sites;
- personal browsing history; and
- personal location information.

Uploading your data to the database does not obligate you to ever use the smart assistant yourself. You have the right to obtain the erasure of your personal data at any time. Please read the following text carefully as the questions are related to this scenario. By giving informed and relevant decision support, the smart assistant decreases the yearly CO_2 emission of each user by approx. 30%. This corresponds to planting 264 trees per year per user. The risk of data being leaked from this type of database is approx. 0.001%. This corresponds to the leakage of data from 1 of 100,000 individuals. Imagine that you could easily upload your personal data to the database anonymously.

You have two options:

You upload your data to the database:

- You contribute to the development of the smart assistant that helps users decrease their CO_2 emission by 30% and, thus, to a sustainable environment.
- You take a 0.001% risk of your data being leaked.

You do not upload your data to the database:

- You avoid a 0.001% risk of your data being leaked.
- You do not contribute to the development of the smart assistant that helps users decrease their CO_2 emission by 30% or to a sustainable environment.

Screenshots of Question Items to Test Hypotheses 1 and 2

How morally wrong is it if people do not upload their personal data to the database?

Click on the slider to answer.

Perfectly fine | Neither fine, nor wrong | Deeply wrong

Do you think it is acceptable to have a law forcing people to upload their personal data to the database?

Click on slider to answer.

Totally unacceptable | Totally acceptable

How inclined are you to upload your personal data to the database?

0% = Not at all likely
100% = Extremely likely

Click on the slider to answer.

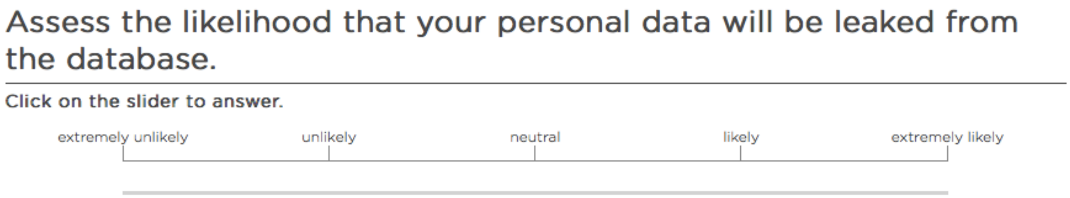
%

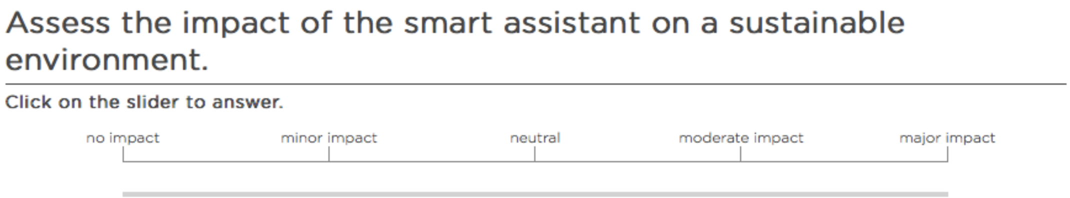
Do you think that there is a moral obligation for people to upload their personal data to the database?

Click on the slider to answer.

It would be wrong for people to upload their personal data to the database | People don't have to upload their personal data to the database, but it would be nice if they did. | People must upload their personal data to the database.

Screenshots of Question Items for Additional Checks (Exemplary for Domain 1)





A2.4 Part 2a of the Experiment

Presentation of the Scenario and Trade-off to Participants (Exemplary for Domain 1 with low Risk and high Impact)

Scenario 2

Imagine that you can decide which particular database to upload your personal data to. You can choose between three available databases. All databases

- require the same personal data,
- have an identical risk of being leaked (0.001%), and
- are used to develop a smart assistant that helps users decrease their CO_2 emission (by 30%).

Database ∆	Database O	Database
Managed by an Ivy League university	Managed by a federal US agency	Managed by a large US tech-company

Screenshots of Question Items to Test Hypothesis 3

How would you rate your relative willingness to upload your personal data to each database?

Please assign points to each of the databases (you have to spend a budget of 100 points).

Database ▫, managed by a large US tech-company	0
Database △, managed by an Ivy League university	0
Database O, managed by a federal US agency	0
Total	0

How would you rate the relative moral obligation for people to upload their personal data to each database?

Please assign points to each of the databases (you have to spend a budget of 100 points).

Database △, managed by an Ivy League university	0
Database ▫, managed by a large US tech-company	0
Database O, managed by a federal US agency	0
Total	0

Do you think it is acceptable to have a law forcing people to upload their personal data to each database?

Click on the slider to answer.

Database O, managed by a federal US agency	Totally unacceptable	Totally acceptable
Database △, managed by an Ivy League university	Totally unacceptable	Totally acceptable
Database ▫, managed by a large US tech-company	Totally unacceptable	Totally acceptable

A2.5 Part 2b of the Experiment

Presentation of the Scenario and Trade-off to Participants (Exemplary for Domain 1 with low Risk and high Impact)

Scenario 2

Data-based personalization is one of the main added values of the smart assistant to give relevant decision support on living healthier. Only by personalizing information is the smart assistant available when and how the user needs it. It is important to consider that the technical nature of the assistant determines how the data are analyzed to derive personalized information (e.g., specific tips and action recommendations). In our scenario, two smart assistants are available.

- Both assistants require the same personal data.
- Both assistants are based on a database with a (20%) risk of being leaked.
- Both assistants help users decrease their probability of getting sick (by 10%).

However, the two assistants differ in their algorithmic rules to derive personalized information such as tips and action recommendations from the database. The initial algorithmic rules of both smart assistants are programmed by a human being. Please read the following descriptions carefully, as it is important that you understand the difference between the two smart assistants.

Smart assistant with a self-learning algorithm (based on database Φ)

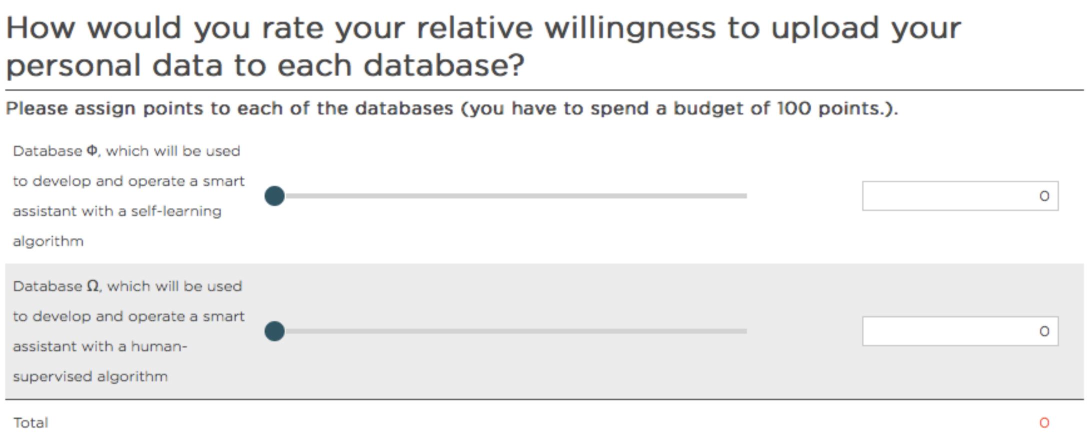
- Rules for personalization autonomously change depending on how the user reacted to past information.
- Consequently, the selected personalized recommendation will

Smart assistant with a human-supervised algorithm (based on database Ω)

- Rules for personalization do not autonomously change depending on how the user reacted to past information; however, a human can manually change the rules.

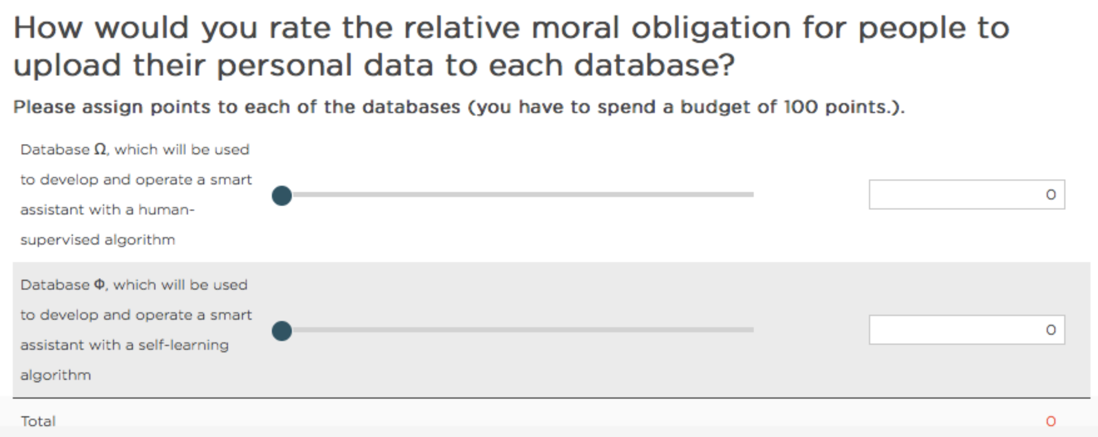
also change over time, depending on the rules the smart assistant automatically modified.	• Consequently, the selected personalized recommendations will change over time, depending on the rules a human manually modified.

Screenshots of Question Items to Test Hypothesis 4 (Plus Comprehension Test)


How would you rate your relative willingness to upload your personal data to each database?

Please assign points to each of the databases (you have to spend a budget of 100 points.).

Database Φ, which will be used to develop and operate a smart assistant with a self-learning algorithm	0
Database Ω, which will be used to develop and operate a smart assistant with a human-supervised algorithm	0
Total	0


How would you rate the relative moral obligation for people to upload their personal data to each database?

Please assign points to each of the databases (you have to spend a budget of 100 points.).

Database Ω, which will be used to develop and operate a smart assistant with a human-supervised algorithm	0
Database Φ, which will be used to develop and operate a smart assistant with a self-learning algorithm	0
Total	0

Do you think it is acceptable to have a law forcing people to upload their personal data to each database?

Click on the slider to answer.

	Totally unacceptable	Totally acceptable
Database Φ, which will be used to develop and operate a smart assistant with a self-learning algorithm		
Database Ω, which will be used to develop and operate a smart assistant with a human-supervised algorithm		

Indicate whether the following statements are true or false.

	True	False
The recommendations of the human-supervised smart assistant depend on how the rules were manually changed by a human.	○	○
The recommendations of the self-learning smart assistant depend on how users reacted in the past and on how the rules automatically changed.	○	○

A2.6 Screenshots of Question Items of Control Variables

Domain- and Treatment-specific Effects

How profit oriented do you think each managing party is?

Click on the slider to answer.

	Not at all	Totally
Ivy League university		
Large US tech company		
Federal US agency		

How trustworthy do you think each managing party is?

Click on the slider to answer.

	Not at all				Totally
Large US tech company					
Ivy League university					
Federal US agency					

Ivy League university

How skilled do you think each managing party is in developing a data-based smart assistant?

Click on the slider to answer.

	Not at all				Totally
Ivy League university					
Large US tech company					
Federal US agency					

Would you want to live in a world with a sustainable environment?

Click on the slider to answer.

Not at all — Totally

Would you want to live in a world where any person living in the United States uploads their personal data to a database in order to promote a sustainable environment?

Click on the slider to answer.

Not at all — Totally

Compared with other people living in the United States, how environmentally friendly would you say that your general lifestyle is?

Click on the slider to answer.

not at all friendly — slightly friendly — somewhat friendly — very friendly — extremely friendly

Would you want to live in a world with a sustainable health system?

Click on the slider to answer.

Not at all | Totally

Would you want to live in a world where any person living in the United States uploads their personal data to a database in order to promote a sustainable health system?

Click on the slider to answer.

Not at all | Totally

Compared to other people your age, how would you say that your general health is?

Click on the slider to answer.

very poor | poor | fair | good | excellent

Diverse Question Items (Demographics and Attitudes)

How old are you?

Please enter your age in years.

How strong are your religious views?

Click on the slider to answer.

Not religious | Very religious

Please answer which statement is rather true for you.

	Really true for me	Sort of true for me	Neutral	Sort of true for me	Really true for me	
Some people have trouble imagining how things might play out over time	○	○	○	○	○	Other people are usually pretty good at seeing in advance how one thing can lead to another
Some people usually think about the consequences before they do something	○	○	○	○	○	Other people just act – they don't waste time thinking about the consequences
Some people like to think about all of the possible good and bad things that can happen before making a decision	○	○	○	○	○	Other people don't think it's necessary to think about every little possibility before making a decision
Some people think it's better to run through all the possible outcomes of a decision in your mind before deciding what to do	○	○	○	○	○	Other people think a lot about how their decisions will affect others
Some people take life one day at a time without worrying about the future	○	○	○	○	○	Other people think it's better to make up your mind without worrying about the future

How much does each party benefit from the decision support by the smart assistant?

Please assign points to each of the parties (you have to spend a budget of 100 points).

The general public	0
The individual user	0
Total	0

For each of the following statements, please indicate the likelihood of engaging in each activity.

Click on the slider to answer.

	Extremely unlikely	Extremely likely
Investing 10% of your annual income in government bonds (treasury bills).		
Investing 10% of your annual income in a blue chip stock.		
Investing 10% of your annual income in a very speculative stock.		
Investing in a business that has a good chance of failing.		

How do you agree with the following statements?

Click on the slider to answer.

	I totally disagree	I totally agree
I would believe advice from the smart assistant even when I don't know for certain that it is correct.		
If I am not sure about a decision, I would have faith that the smart assistant will provide the best solution.		
When I am uncertain about a decision I would believe the smart assistant rather than myself.		
When the smart assistant gives unusual advice, I would be confident that the advice is correct.		

What is your highest level of education?

Please select

Are you a US citizen?

Yes No

Generally speaking, would you say that most people can be trusted, or that you can't be too careful in dealing with people?

Click on the slider to answer.

You can't be too careful in dealing with people — Most people can be trusted

What describes your standard of living?

Click on the slider to answer.

Poor — Very well off

How do you agree with the following statements?

Click on the slider to answer.

	I totally disagree — I totally agree
The smart assistant uses appropriate methods to reach decisions.	
The advice the smart assistant produces is as good as the advice, which a highly competent person could produce.	
The smart assistant has sound knowledge about the type of problem built into it.	
The smart assistant correctly uses the information from the database.	

In political matters, people talk of 'the left' and 'the right'. How would you place your views on this scale, generally speaking?

Click on the slider to answer.

left | right

What is your annual income, including tips, dividends, interest etc. (in US dollars)

Please select

What is your gender?

Please select

Please answer which statement is rather true for you.

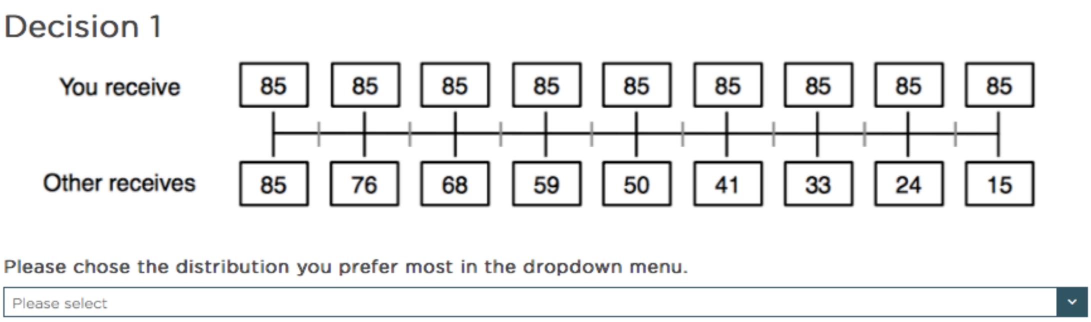
	Really true for me	Sort of true for me	Neutral	Sort of true for me	Really true for me	
Some people take life one day at a time without worrying about the future	○	○	○	○	○	Other people are always thinking about what tomorrow will bring
Some people often think what their life will be like ten years from now	○	○	○	○	○	Other people don't even try to imagine what their life will be like in 10 years
Some people would rather save their money for a rainy day than spend it right away on something fun	○	○	○	○	○	Other people would rather spend their money right away on something fun than save it for a rainy day
Some people would rather be happy today than take their chances on what might happen in the future	○	○	○	○	○	Other people will give up their happiness now so that they can get what they want in the future
Some people spend very little time thinking about how things might be in the future	○	○	○	○	○	Other people spend a lot of time thinking about how things might be in the future

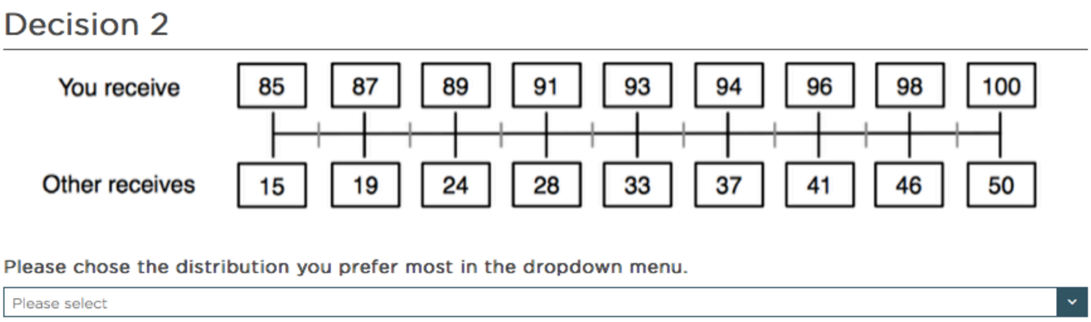
A2.7 Monetary Incentivized Question Items

Social Value Orientation

Instructions

In this task, you are actually paired with another real person, whom we will refer to as the other. This other person is someone you do not know and will remain mutually anonymous. All of your choices are completely confidential. You will be making a series of decisions about allocating resources between you and this other person. For each of the following questions, please indicate the distribution you prefer most by choosing the respective allocation in the dropdown menu. Your decisions will yield an additional payment for both yourself and the other person. The maximum additional payment for you and the other person is $0.10. Additional payments will be allocated between you and the other person depending on which allocations you choose in the dropdown menus below. 100 points represent $0.01. In case of odd numbers, we will round up in your favor. There are no right or wrong answers, this is all about personal preferences.





Decision 3

You receive	50	54	59	63	68	72	76	81	85
Other receives	100	98	96	94	93	91	89	87	85

Please chose the distribution you prefer most in the dropdown menu.

Please select

Decision 4

You receive	50	54	59	63	68	72	76	81	85
Other receives	100	89	79	68	58	47	36	26	15

Please chose the distribution you prefer most in the dropdown menu.

Please select

Decision 5

Page 1

You receive	100	94	88	81	75	69	63	56	50
Other receives	50	56	63	69	75	81	88	94	100

Please chose the distribution you prefer most in the dropdown menu.

Please select

Decision 6

You receive	100	98	96	94	93	91	89	87	85
Other receives	50	54	59	63	68	72	76	81	85

Please chose the distribution you prefer most in the dropdown menu.

Please select

Behavior of Others

How many out of every 100 people taking part in this survey say they would be rather willing (=a higher value than 50 on the previous 100-slider) to provide their personal data to the database?

Please note: if you estimate the right number (+/– 5 respondents), you will receive an additional payment of $0.05.

0 people

B Appendix to Chapter 4.2

Information zur Umfrage

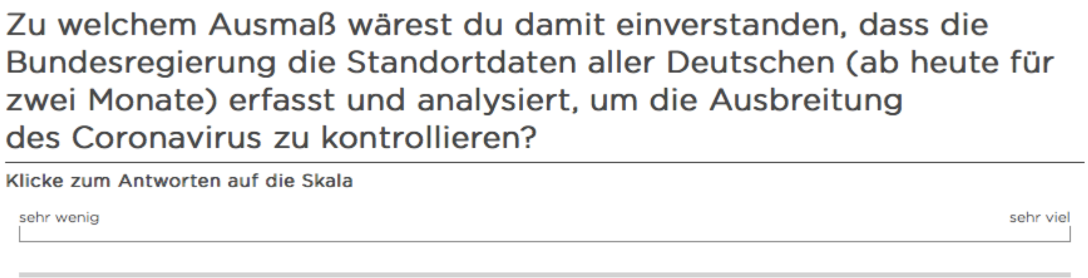
In dieser Umfrage geht es um die Erfassung und Analyse von Standortdaten, um die Ausbreitung des Coronavirus zu kontrollieren. Die Teilnahme an der Umfrage dauert ca. 3 Minuten, wird nicht vergütet und von Kirsten Hillebrand (Universität Bremen) durchgeführt.

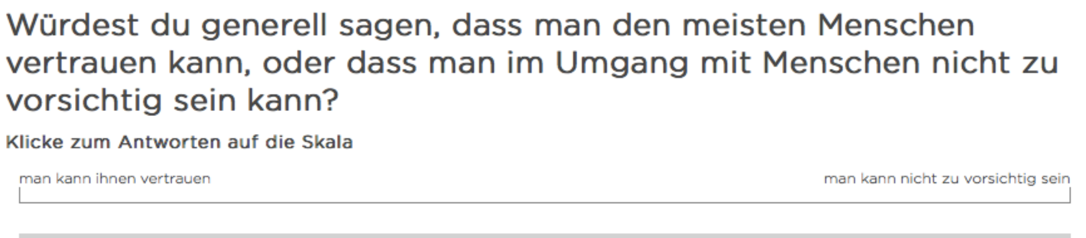
Deine Antworten werden in anonymisierter Form ausgewertet. Dein Name wird nicht erfasst. Die Ergebnisse der Umfrage können auf wissenschaftlichen Tagen präsentiert, in wissenschaftlichen Zeitschriften veröffentlicht oder auf eine anderer Weise anonymisiert an die wissenschaftliche Gemeinschaft weitergegeben werden. Wenn du auf das untenstehende Kästchen klickst, bedeutet das, dass du diese Hinweise gelesen hast und freiwillig an der Umfrage teilnimmst.

Wenn du weitere Fragen zum Hintergrund der Studie, zu deiner Datenspeicherung oder etwas anderem hast, schreibe eine Mail an kihi(at)uni-bremen.de.

[Checkbox] Ich stimme zu, dass meine Umfrage-Daten wie oben beschrieben verarbeitet werden dürfen.

Screenshots of the Survey Items





Zu welchem Ausmaß hast du Angst vor den Folgen des Coronavirus für dich und den dir am nächsten stehenden Menschen?

Klicke zum Antworten auf die Skala

sehr wenig sehr viel

Zu welchem Ausmaß hast du Angst vor den Folgen des Coronavirus für die deutsche Bevölkerung?

Klicke zum Antworten auf die Skala

sehr wenig sehr viel

Zu welchem Ausmaß glaubst du, dass die Bundesregierung die Standortdaten auch tatsächlich nutzen würde, um die Ausbreitung des Coronavirus zu kontrollieren?

Klicke zum Antworten auf die Skala

sehr wenig sehr viel

Bist du bereit, fünf weitere Fragen zu beantworten, damit wir deine obigen Angaben besser verstehen?

○ Nein ○ Ja

33% WEITER

Geschlecht

Bitte auswählen

Bitte auswählen

Männlich

Sonstige

Weiblich

Netto Jahreseinkommen einschließlich Trinkgeld, Zinsen, Dividenden etc.

Bitte auswählen

- unter 5.000€
- 5.000€ - 10.000€
- 10.001€ - 15.000€
- 15.001€ - 25.000€
- 25.001€ - 35.000€
- 35.001€ - 50.000€
- 50.001€ - 80.000€
- 80.001€ - 100.000€

Wie alt bist du?

in Jahren

Was ist dein höchster erreichter Bildungsabschluss?

Bitte auswählen

- Bitte auswählen
- Weniger als Abitur
- Abitur
- Berufsausbildung
- Studium begonnen
- Bachelor
- Master/ Diplom/ Doktor
- Sonstiges

Was sind deine politischen Ansichten?

Klicke zum Antworten auf die Skala

links | rechts

C Appendix to Chapter 4.3

Survey Items on Desire and Intention for Behavioral Change

Mein Bedürfnis, mich nach dem Wettbewerb klimafreundlicher als davor zu verhalten, ist... *

	1	2	3	4	5	
schwach	◯	◯	◯	◯	◯	stark

Ich plane, mich in den nächsten zwei Wochen klimafreundlicher zu verhalten, als ich es vor dem Wettbewerb getan habe. *

	1	2	3	4	5	
trifft nicht zu	◯	◯	◯	◯	◯	trifft zu

Ich plane, mich in den nächsten zwei Wochen klimafreundlicher zu verhalten, als ich es vor dem Wettbewerb getan habe. *

	1	2	3	4	5	
trifft nicht zu	◯	◯	◯	◯	◯	trifft zu

Ich werde mich während der nächsten zwei Wochen klimafreundlicher verhalten, als ich es vor dem Wettbewerb getan habe. *

	1	2	3	4	5	
sehr unwahrscheinlich	◯	◯	◯	◯	◯	sehr wahrscheinlich

Survey Items on SUS Score

Ich denke, dass ich die App gerne nochmal benutzen würde. *

	1	2	3	4	5	
Stimme überhaupt nicht zu	○	○	○	○	○	Stimme voll zu

Ich fand die App unnötig komplex. *

	1	2	3	4	5	
Stimme überhaupt nicht zu	○	○	○	○	○	Stimme voll zu

Ich glaube, ich würde die Hilfe einer technisch versierten Person benötigen, um die App benutzen zu können. *

	1	2	3	4	5	
Stimme überhaupt nicht zu	○	○	○	○	○	Stimme voll zu

Ich kann mir vorstellen, dass die meisten Menschen den Umgang mit der App sehr schnell lernen. *

	1	2	3	4	5	
Stimme überhaupt nicht zu	○	○	○	○	○	Stimme voll zu

Ich musste eine Menge lernen, bevor ich anfangen konnte die App zu verwenden. *

	1	2	3	4	5	
Stimme überhaupt nicht zu	○	○	○	○	○	Stimme voll zu

Ich fand die App sehr umständlich zu nutzen. *

	1	2	3	4	5	
Stimme überhaupt nicht zu	◯	◯	◯	◯	◯	Stimme voll zu

Ich fühlte mich bei der Benutzung der App sehr sicher. *

	1	2	3	4	5	
Stimme überhaupt nicht zu	◯	◯	◯	◯	◯	Stimme voll zu

Survey Items on Behavior Change during App Usage

Welche der Taten hast du während des Wettbewerbs öfter durchgeführt als sonst?

- ☐ vegetarisch oder vegan Mittag gegessen
- ☐ weniger geheizt
- ☐ mit KollegInnen über Nachhaltigkeit ausgetauscht
- ☐ PC, Monitor & Licht ausgeschaltet
- ☐ Rad zur Arbeit genommen
- ☐ Fahrgemeinschaften gebildet
- ☐ Spritsparend gefahren
- ☐ Bahn (RE, ICE) genutzt
- ☐ To-Go Müll vermieden
- ☐ ÖPNV zur Arbeit genommen