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Acceptance of Data Sharing in Smartphone Apps from Key Industries of the Digital Transformation: A Representative Population Survey for Germany

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Acceptance of data sharing in smartphone apps from key industries of the digital transformation: A representative population survey for Germany

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Abstract

The use of smartphone apps has numerous advantages for app providers and users. However, the users of many smartphone apps are confronted with a trade-off between usage benefits and preferences for personal data protection. We investigate the acceptability of data sharing in different hypothetical scenarios describing five types of these apps from key industries of the digital transformation. In a representative survey for the German population ($N = 1{,}013$), we examine to what extent the acceptance of data sharing is influenced by potential recipients, collected information attributes, and the promoted benefits of data sharing. We differentiate the promoted benefits in two treatments according to monetary (or personal) and environmental (or public) benefits. Our results show no treatment effects but significant differences in acceptance values for different recipients and information attributes. We further observe that participants with stronger green consumption values, participants with a stronger risk propensity, men, and younger participants show a higher acceptance towards data sharing in the described scenarios.

Keywords: privacy, digitalization, digital transformation, representative survey, data protection, environmental attitudes

JEL Codes: O33, Q18, C83, L86, M31, M37

1. Introduction

In the course of the Covid-19 pandemic, governments in various countries have developed digital contract tracing apps. The aim of these apps has been to inform people about possible risk contacts and thus help to slow down the spread of the pandemic. In Germany, large parts

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of the society have had a positive attitude towards the app. At the same time, intensive debates on various data protection concerns arose even before the apps were launched (Altmann et al., 2020; Amann et al., 2020; Rowe, 2020). The example of the Covid-19 tracing app illustrates important privacy relevant characteristics of apps and at the same time reveals problems that app providers face on a regular basis. Many apps require consumers to disclose personal information to actors of the private or public sector in order to use the apps and the benefits they offer. For the data-providing consumers, there is consequently a trade-off between preferences for their own data protection and the potential benefits of data disclosure (Acquisti et al., 2020, 2016, 2015; Kokolakis, 2017). For app providers, it is essential to know which features of an app influence users' privacy preferences to what extent. Without such knowledge, users' privacy concerns may not be adequately addressed, and users may be skeptical about using an app or could decide against using an app at all. Since individuals' online privacy preferences are highly heterogeneous (Acquisti et al., 2020, 2016, 2015) and context specific (John et al., 2011) knowledge on specific acceptance drivers is crucial.

Acquisti et al. (2016) describe the disclosure of personal data and the protection of this data as two sides of the same coin. The disclosure of personal data is associated with benefits for the consumers who provide the data, e.g., in the form of financial savings when purchasing products or from bonus payments. By using apps, consumers can reduce search costs during shopping and adapt their consumption behavior in order to match their own preferences. Companies benefit because they can increase their profits by collecting information from their consumers. In this way, companies can efficiently utilize existing consumer potential and save resources, for instance, by avoiding excessive advertising. However, for consumers, the disclosure of personal data can also lead to negative consequences, such as identity theft (Moore et al., 2009), discrimination of various kinds (Cui et al., 2020; Edelman et al., 2017), or a burden through excessive advertising (Johnson, 2013). Companies can also suffer from disadvantages, such as costs resulting from data theft (Hinz et al., 2015), or misuse of data by members of their own company or by members of affiliated companies (Acquisti et al., 2016).

Since the early 2000s, various scientific studies have investigated which factors influence privacy preferences in different contexts (for overviews of these studies see Acquisti et al., 2020, 2016, 2015; Kokolakis, 2017). The results of these studies show, for instance, that the willingness to share data is influenced by the number of potential recipients (Schudy and Utikal, 2017), the content of the data collected (Cloos et al., 2019; Benndorf and Normann, 2018; Schudy and Utikal, 2017), and the survey framing

(John et al., 2011). In the context of digital transformation, Apthorpe et al. (2018) use an advanced survey method to examine privacy norms in various smart home settings. The survey method builds on the theory of Contextual Integrity (Nissenbaum, 2009) which states that data protection standards are context-specific and face the generally accepted adequacy of a specific information exchange. Apthorpe et al. (2018) divide the contexts into the parameters sender, receiver, information attribute, transmission attribute or benefit associated with data transmission, and subject, which enables them to combine different information flows. In this way, the authors identify that in certain smart home contexts even the change of a single parameter can have a significant impact on a data protection standard. For example, participants indicate, on average, considerably higher acceptance values for a fitness tracker sharing data on the heart rate of its owner than sharing data on the eating habits of its owner.

Although knowledge about the acceptance of data sharing in specific digital technologies is important for companies, regulatory authorities, and research, this topic has rarely been investigated in real life settings. Laboratory or field experiments on privacy usually focus on single contexts or on completely artificial situations (see Kokolakis, 2017). While the survey investigation by Apthorpe et al. (2018) explicitly refers to the smart home context, little is known about factors that influence the acceptance of data sharing in the industries most affected by digital transformation. For example, previous research has not addressed the question whether specific external benefits of apps lead to higher acceptance for data sharing. Furthermore, there is comparatively little evidence on how acceptance of data sharing is shaped by various socio-demographic factors and personal attitudes.

This paper investigates the acceptance of data sharing in apps for five key industries of digital transformation. The selected industries are retail, health, nutrition, mobility, and energy. With a representative survey ($N = 1{,}013$) for the German population we examine in hypothetical but realistic scenarios, how the acceptance of data sharing via apps varies depending on potential recipients (e.g., market research companies, employer, or federal ministries) and information attributes (e.g., live location, nutrition style, or monthly net income). Wright et al. (2014: 325) point out that "…scenarios are a useful instrument to provoke policy-makers and other stakeholders, to including industry, in considering the privacy, ethical, social and other implications of new and emerging technologies." For each scenario within the survey, we first give a brief and concise explanation of what the app does, who the app provider is, what information attributes must be mandatorily provided in order to use the app, and what benefits the app offers. Then, participants have to assess for further optional data recipients how acceptable it is that the information collected with the app will be shared with these recipients. In the final step, participants have to evaluate for various optional information attributes how acceptable it is that these attributes are collected via the app.

The extent to which green advertising strategies and green consumption values affect the privacy preferences of consumers has not been investigated in the literature so far. We therefore collect acceptance values in two different treatments. The treatments differ according to whether the transmission of data is primarily highlighted by monetary (or personal) or by environmental (or public) benefits. The additional collection of demographic variables and personal attitudes to privacy, sustainable consumption, and risk allows us to analyze how these factors affect the acceptance of data sharing. Our method is adapted from Apthorpe et al. (2018). However, with the decisive difference that our study covers five different industries, and in this way demonstrates how the method developed by Apthorpe et al. (2018) can be applied in a wide range of other contexts.

Our results show no treatment effects for recipients and information attributes. In all scenarios, average acceptance values for data sharing differ significantly between different recipients and information attributes. Acceptance values are particularly low for recipients and information attributes that have a low thematic fit with the respective scenario and where data sharing can potentially lead to very negative consequences. We further observe that the acceptance towards data sharing is lower for stronger online privacy preferences and higher for a larger risk propensity and for stronger green consumption values.

The findings of our paper can help app providers from various industries to identify and address sensitive privacy areas and thereby successfully realize the potential of their existing and planned apps. Our paper additionally provides important insights for public authorities and consumer protection agencies that can be used to adequately address consumers' privacy protection issues. Our results also provide impulses for further scientific research in the fields of privacy and (managing) digital transformation.

2. Method

2.1 Scenario development

As mentioned above, Apthorpe et al. (2018) identify various Internet of Things (IoT) applications in the context of smart homes as a relevant area for research on privacy standards. Acquisti et al. (2016) find that online advertising, price discrimination in different industries, health care, and finance (lending) are relevant areas where a trade-off between benefits through data provision and privacy preferences exists. Online dating platforms, sharing services such as *AirBnB,* and recruitment processes are further mentioned as relevant areas.

The hypothetical scenarios in this study refer to industries that are largely affected by the digital transformation. We selected the industries according to the following criteria: First, each industry should have a connection to daily consumption, shopping, or health behavior. In this way, we intended to ensure that the scenarios described did not appear too abstract to our participants and that the majority of participants were at least partially familiar with the content of the scenarios. Second, in each industry, (tracking) apps should already exist or at least be conceivable. Finally, these apps should bring benefits to customers, but also require sharing personal data. Related literature underlines the increasing importance of smart technologies (e.g., smartphone apps) in our selected industries - retail (e.g., Roy et al., 2017), health (e.g., Tresp et al., 2016), nutrition (e.g., O'Sullivan et al., 2018), mobility (e.g., Del Vecchio et al., 2019), and energy (e.g., Horne et al., 2015). The relevance of the selected industries is further highlighted by the fact that the German digital association Bitkom identifies retail, health, mobility, and energy as key industries of digital transformation (Bitkom, 2020)[1].

In a review paper on scenario planning, Amer et al. (2013) identify internal consistency, plausibility, creativity, and relevance as the most important validation criteria. The scenario development in our study is based on these criteria. In the descriptions of our scenarios, we use a logical and coherent structure in order to achieve a high degree of internal consistency (see Appendix A). As we explain in section 2.1.1, the apps and technologies in our scenarios are derived from existing apps and technologies. To guarantee a high level of plausibility, we made sure that the information flows we describe are conceivable. Relevance is ensured by basing our study design on the current literature on smart technologies, digital transformation, data analytics, and privacy. Creativity is achieved by describing apps with different functionalities from different industries.

Table 1 presents the parameters used in our scenarios. A detailed description of each scenario can be found in Appendix A (Tables 5 to 9). In the following, we provide a rationale for the selected sending device and provider combinations, recipients, information attributes, and transmission benefits.

[1] Bitkom (2020) further includes the agricultural industry. In our study, we integrate the food industry to ensure consumer orientation.

<table>
<tr><th colspan="2">Scenario and Provider</th><th>Sending device</th><th>Information attributes (mandatory)</th><th>Recipients (optional)</th><th>Information attributes (optional)</th><th>Transmission benefit</th></tr>
<tr><td>A</td><td>Super-market</td><td>Loyalty card with app</td><td>- Name
- Adress
- Date of Birth</td><td rowspan="5">- Household members[A,B,C,D,E]
- Employer[A,B,C,D,E]
- Federal ministries [A,B,D,E]
- Market research companies[A,B,C]
- German food producers[A,C]
- Local and long-distance public transport companies[D,E]
- City or municipality[D,E]
- Health insurance company[A]
- American food producers[A]
- Chinese food producers[A]
- German sports equipment producers[B]
- German Society for Nutrition[C]
- Neighbors[E]</td><td rowspan="5">- Live location[A,B,C,E]
- Monthly net income[C,D,E]
- Nutrition style[A,B]
- Body weight and height[A,B]
- Food intolerances and allergies[A,C]
- Memberships in a sports club or gym[B,C]
- Profession[D,E]
- Number of steps taken[A]
- Date of birth[D]
- Driving behavior[D]
- Use of power sources[E]</td><td>Product recommendations (T1), Waste avoidance (T2)</td></tr>
<tr><td>B</td><td>Health insurance company</td><td>Tracking bracelet with app</td><td>- Name
- Date of birth
- Gender</td><td>Bonus payment (T1),
Tree sponsorship (T2)</td></tr>
<tr><td>C</td><td>Federal ministry of health</td><td>Nutrition app</td><td>- Name
- Date of birth
- Gender
- Body weight and height
- Nutritional style</td><td>Nutritional recommendations: Health-promoting (T1), Env. friendly (T2)</td></tr>
<tr><td>D</td><td>Techno-logy start-up company</td><td>Mobility-tracking app</td><td>- Name
- Gender
- Live location
- Type of vehicle</td><td>Mobility recommendations: Cost- and time saving (T1), Env. friendly (T2)</td></tr>
<tr><td>E</td><td>Energy provider</td><td>Smart meter with app</td><td>- Name
- Address
- Date of birth</td><td>Power usage recommendations: Cost reducing (T1), Env. friendly (T2)</td></tr>
</table>

Table 1: Description of the individual scenarios in terms of provider, sending device, optional recipients, mandatory and optional information attributes, and transmission benefits.
Note: The superscript letters at recipients (optional) and information attributes (optional) indicate in which scenarios (A to E) the respective recipients or information attributes are included.

2.1.1 Sending device and provider

Based on the above-mentioned literature and further non-scientific reports, we selected five sending device and provider combinations. The criteria for each of these combinations were that they are (1) realistic and relevant for the respective industry and (2) that the devices include a possibility of being connected to an app. In the first sentence of each scenario we explained that the respective app is cost-free. For the choice of providers and recipients, we deliberately selected private companies, public companies, and governmental actors. In line with Apthorpe et al. (2018), we did not mention specific device names in order to avoid associations with existing devices. Our five sending device and provider combinations are:

A. **Loyalty card with app from supermarket chains:** In the retail industry, single companies or coalitions of companies offer loyalty cards in combination with apps and thereby collect information about the product selection and purchasing behavior of their customers (Wang et al., 2018). Based on this information, customers can receive individualized product recommendations or discounts via these apps (Cortiñas et al., 2008). Both the timing and the topic can be specifically targeted towards customers in order to achieve the greatest possible effectiveness of the product recommendations and advertisements (Fernández-Rovira et al., 2021; Acquisti et al., 2016). Smart retail technologies can improve customers' shopping experience (Minch, 2015), e.g., through personalization, but at the same time they also raise privacy concerns (Roy et al., 2017). For companies, like supermarket chains, customer-oriented technologies are an essential tool to attract new customers and to stimulate the purchasing behavior of existing customers (Inman and Nikolova, 2017). Loyalty cards are widely used and well-known in German retail. Our retail scenario is very similar to the loyalty program Payback[2]. In Germany, more than 31 million people currently use the Payback card and 10 million of them actively use the Payback app (Payback, 2020). In our retail scenario, the app providers (supermarket chains) are from the private sector.

B. **Tracking bracelet with app from a health insurance company:** Digitalization affects the healthcare system in various ways (see e.g., Tresp et al., 2016; Agarwal et al., 2010). Fitness tracking apps are not only used to improve the quality and cost of healthcare (Mehta and Pandit, 2018), but are also applied to self-track sport activities and one's personal health (Williamson, 2015). However, in addition to these benefits, sharing personal fitness data and health data can also raise privacy concerns (Vitak et al., 2018) or lead to discrimination among minorities (Joy et al., 2020). German health insurance companies already use data from app-based activity trackers and provide premiums based on this data (Techniker Krankenkasse, 2020). In a representative study for Germany, the market research company Splendid Research (2019) found that 33% (23%) of the German population uses (is interested in) apps or wearables to track personal fitness, health, or nutrition data. 38% of the respondents totally reject the use of these self-measurement systems. The results of the survey further showed that more than half of the participants would share health-related data with health insurance companies in order to obtain discounts. In our scenario, we did not specify whether the health insurance company is a private or statutory health insurance, since in the German multi-payer healthcare system more than 69 million people (> 83% of the German population) are insured by statutory health insurance companies (Bundesministerium für Gesundheit, 2019: 109).

C. **Nutrition app from the Federal Ministry of Health:** As consumer behavior changes towards self-optimization, there is also a demand for food products that are tailored to

[2] Payback is a multinational and multi-industry bonus system with a customer card and the leading bonus program in Germany (Payback, 2020).

individual needs (O'Sullivan et al., 2018; Poutanen et al., 2017). Artificial intelligence and smartphone apps enable practical and personalized nutritional recommendations based on genetic and behavioral information such as eating behavior and physical activity. These nutritional recommendations can help, for instance, to prevent obesity or diseases such as diabetes (Chatelan et al., 2019). In the field of nutrition, there are various apps that enable users to count calories, track their purchased food using barcode scanners, or create personalized nutrition plans. Often these apps can also be combined with other fitness apps (for an overview see DiFilippo et al., 2015). In our nutrition scenario, the app provider (Federal Ministry of Health) is a governmental institution.

D. **Mobility tracking app from a technology start-up company:** Smartphone based tracking in the mobility sector enables to improve urban planning and transport systems and to effectively satisfy people's travel needs (Longhi and Nanni, 2020; Wahlström et al., 2017; Gisdakis et al., 2014; Guido et al., 2012, Mohan et al., 2008). Behavioral changes can be induced by providing consumers with personalized transport solutions. However, mobility tracking requires consumers to disclose sensitive data, such as their live location, which potentially entails privacy concerns (Bucher et al., 2019; Cellina et al., 2019; Del Vecchio et al., 2019; Iqbal and Lim, 2010). Mobility tracking is comparatively less popular in Germany than in other countries. The tracking of car driving behavior to determine user-dependent insurance rates, known as telematics (Longhi and Nanni, 2020; Wahlström et al., 2017), is estimated to be used by less than 1% of all car drivers in Germany.[3] In 2016, by contrast, 17% of Italian, 10% of South African, and 6% of US car drivers had already signed up to telematics-based insurance policies.[4] In our mobility scenario, the app provider is a technology start-up from the private sector.

E. **Smart meter with app from an energy provider:** A smart meter is an intelligent digital electricity meter that records and stores data on power consumption at any time and can also send the stored data (Zheng et al., 2013). Since energy consumption data is automatically and frequently transmitted to the energy provider, smart meters have the potential to raise privacy concerns (Horne et al., 2015). Greveler et al. (2012) show that high-resolution data on a household's energy consumption enables undesired identification and monitoring of the appliances used in the consumer's home. Since 2020, Germany has an obligation to install smart meters if annual electricity consumption exceeds 6,000 kWh.

[3] See (in German) https://www.capital.de/geld-versicherungen/telematik-tarife-der-versicherer-faehrt-mit, accessed December 01, 2020.

[4] See https://www.mckinsey.com/industries/automotive-and-assembly/our-insights/telematics-poised-for-strong-global-growth, accessed December 01, 2020.

From the year 2032 onwards, smart meters will be mandatory for all households (Bundesministerium für Wirtschaft und Energie, 2020). Energy providers in Germany are often publicly owned companies. However, due to space reasons we refrained from a more specific description of the company in our scenario.

2.1.2 Recipients and information attributes

For our scenarios, we selected a broad range of different organizations and groups as potential recipients of the collected information. In each scenario, the participants were asked to what extent they find it acceptable that the information collected by the sending device is shared with optional recipients, in addition to the app provider. After that, the participants were asked to what extent they find it acceptable that the app provider requests and collects optional information attributes with the app in addition to the set of information attributes which has to be mandatorily provided when using the app. In each scenario, we described that possible data sharing with optional recipients and the possible request and collection of optional information attributes was clearly stated in the app's general terms and conditions.

We aimed to provide a good balance for the selected recipients and information attributes and therefore always selected recipients and information attributes for which we expected comparatively high and comparatively low acceptance values. In general, we chose recipients and information attributes that, at least in a broad sense, thematically fitted the respective scenario. We aimed to avoid that the scenarios appeared too unrealistic to the participants since this might have resulted in high dropout rates. For this reason, some optional recipients and information attributes were only included in one or two scenarios while others were included in each scenario.

2.1.3 Transmission benefits

As outlined above, the provision of apps through companies and other organizations can help them to use resources more efficiently and at the same time to purposefully address the needs of their customers or target groups. For users, apps similar to those in our scenarios often provide information and offers that can result in cost and time savings. In each of our scenarios, we described specific benefits that result from data sharing in the respective app. In treatment 1 (T1) monetary (personal) benefits, such as bonus payments or personalized cost-saving behavior recommendations for the app user, were mentioned. In contrast, treatment 2 (T2) mentioned environmental (public) benefits, such as nature-friendly activities through the app provider, that increase when the app is used by a larger number of people or personalized environmentally friendly behavior recommendations for the app user.

2.2 Survey design

Our survey consisted of four stages (Figure 1). In stage 1, socio-demographic questions on gender, age, residence (federal state), and education were asked in order to verify the quotas of the representative survey.[5] Then, the participants were exposed to five hypothetical scenarios in stage 2. Before presenting the scenarios, participants were randomly allocated into two treatment groups.

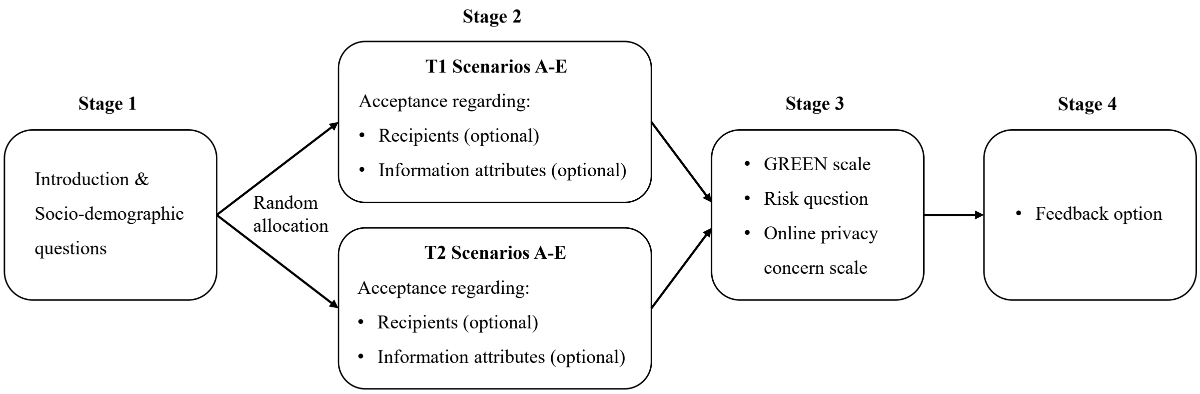

Figure 1: Sequence of the survey.

Participants completed all scenarios in either T1 or T2. We used this between subjects design in order to prevent participants from anticipating our research objective. If participants had noticed that we wanted to investigate the effects of monetary and environmental benefits on the acceptance of data sharing, these participants could have adjusted their response behavior accordingly which could bias our results. The sequence of the scenario presentation corresponded to the described conceptualization in section 2.1. In each scenario, participants had to assess the acceptance of data sharing with (1) optional recipients and (2) for optional information attributes. The different recipients and information attributes were presented in a random order.

In total, each participant had to assess the acceptance of 30 recipients and 21 information attributes in 10 boxes. In each scenario, the first box contained different recipients, followed by a second box with information attributes. This order should ensure that participants only considered mandatory information attributes, rather than optional ones, when assigning acceptance values to recipients. Acceptance was measured on a six-level scale from (1) completely unacceptable, (2) somewhat unacceptable, (3) rather unacceptable, (4) rather acceptable, (5) somewhat acceptable to (6) completely acceptable. In order to illustrate our results in section 3 as clearly as possible, we converted the original values of our six-level

[5] The quotas were calculated based on the database (Genesis online) of the Federal Statistical Office of Germany.

acceptance scale into a range from -1 to 1. Therefore, the negative range includes the values (-1) completely unacceptable, (-0.6) somewhat unacceptable, and (-0.2) rather unacceptable, whereas the positive range includes the values (0.2) rather acceptable, (0.6) somewhat acceptable, and (1) completely acceptable. We deliberately refrained from providing a central answer option in order to avoid an anchor effect towards the middle and to force participants to make explicit acceptance decisions.

In stage 3, participants' attitudes were assessed by using well-validated measures.[6] To collect data on participants' sustainable consumption attitudes, we used the six-item GREEN consumption scale (Haws et al., 2014). We included a quality check question to this scale in order to expose those respondents who did not seriously answer our survey. Participants' online privacy concern was assessed by using a six-item scale by Ham (2017) adapted from Dolnicar und Jordaan (2007). Both latent constructs were measured on seven-point Likert scales ranging from (1) strongly disagree to (7) strongly agree. Lastly, we measured participants' risk attitude by using a single question proposed by Dohmen et al. (2011). Stage 4 closed the survey with a field for optional comments.

2.3 Hypotheses

2.3.1 Treatment effects

Our first set of hypotheses focuses on possible treatment effects. Over the past couple of years, it has been observed that companies frequently underline their environmental or social commitment within their product advertisements. One prominent example is the rainforest project of the German Krombacher brewery. In cooperation with the World Wildlife Fund (WWF), the brewery promotes its products by saying that customers save one square meter of rainforest by buying a box of beer (Mögele and Tropp, 2010). In a field experiment, Asensio and Delmas (2016, 2015) observe that participants adopt a more environmentally friendly energy consumption behavior if they receive information on the environmental and health impact of their households' energy consumption behavior. In contrast, only small or no changes in consumption behavior can be found when participants receive information on the financial benefits of a more efficient energy consumption behavior. In our study, we expect participants to view data sharing as more acceptable if the environmental benefits of apps are highlighted. We further expect acceptance values to be higher in T2, as participants may consider data sharing in T2 more acceptable due to image concerns (Ariely et al., 2009). In T2, participants

[6] Details of both measurement scales are described in Appendix D.

could tend to evaluate the apps described in the scenarios as more acceptable to express their prosocial and environmentally friendly attitude towards their social environment through these apps. Therefore, our first two hypotheses are:

H1.1: Acceptance values for data sharing with optional recipients are higher in T2 than in T1.

H1.2: Acceptance values for data collection of optional information attributes are higher in T2 than in T1.

2.3.2 Data recipients

Concerning potential data recipients, Apthorpe et al. (2018) use the immediate family members as baseline and argue that immediate family members usually have knowledge about the information that can be transmitted in their IoT scenarios. For example, immediate family members know from each other which travel vehicles are used or whether they do sports. Consistent with this argumentation, the authors observe the highest acceptance values for immediate family members. For the scenarios in our survey, we also assume that the highest acceptance values for data sharing are indicated for the recipient *household members*. On the contrary, we expect the lowest acceptance values to be indicated for the recipient *employer*. Persson and Hansson (2003) discuss several reasons why employers may have an interest in invading the privacy of their employees. At the same time, employees can have numerous reasons why they would not want to share private information such as information collected in apps with their employers. In a study on the rating environment and platform design of employer review platforms, Cloos (forthcoming) argues that employees, due to their economic dependence on employers, have strong incentives to refrain from too permissive data sharing on the internet. For the scenarios in our survey, it also seems plausible that participants fear negative consequences if data is shared with employers. Although numerous negative consequences are also conceivable when data is shared with other recipients, these consequences are less dramatic than a possible job loss which might be the result of data sharing with employers. Therefore, our next hypotheses are:

H2.1: Acceptance values for *household members* are higher than acceptance values for the other optional recipients.

H2.2: Acceptance values for *employer* are lower than acceptance values for the other optional recipients.

2.3.3 Information attributes

Unlike for recipients, our scenarios do not include information attributes that are queried in all scenarios. When formulating the hypotheses on the acceptance towards data collection of optional information attributes, we exclusively concentrate on the *live location* and the *monthly net income*, since these information attributes are included in more than half of the scenarios. Live location data raise (serious) security and privacy concerns (Minch, 2015). In Apthorpe et al.'s (2018) study, the sharing of the live location by different IoT transmitters is evaluated as relatively unacceptable. The results of a qualitative study by Muslukhov et al. (2012) also show that smartphone users perceive location tracking as very sensitive. In line with this literature, we expect that the acceptance values regarding a transmission of the live location are very low in our study. With regard to data collection of the *monthly net income*, we also expect very low acceptance values. In Germany, it is relatively unusual to talk about one's own income. People tend to not want to talk about their own income and also feel that they should not talk about it (for a discussion of related surveys, see Sauerland and Höhs (2019) (in German)). Hence, we derive the following hypotheses:

H3.1: Acceptance values for *live location* and *monthly net income* are lower than acceptance values for the other optional information attributes.

H3.2: Acceptance values do not differ between *life location* and *monthly net income*.

2.3.4 Attitudes

The fourth set of hypotheses refers to respondents' attitudes on privacy, risk, and green consumption. To measure the privacy preferences of our participants, we use the scale by Ham (2017). The items of this scale ask for consent to collect data on participants' online behavior. Since the questions in our study refer to a very similar subject area, we expect higher values on the privacy scale to be associated with lower acceptance values. With regard to participants' risk attitudes, we expect that a higher willingness to take risks is associated with higher acceptance values. In a study on the privacy paradox (i.e., a potential privacy intentions behavior gap), Norberg et al. (2007) find that a higher risk aversion is associated with a lower willingness to provide personal data. Further research (Fogel and Nehmad, 2009) shows that individuals who use social networks are more willing to take risks than individuals who do not use social networks. To the best of our knowledge, there are no studies that investigate the relationship between green consumption values and privacy preferences. Therefore, we deliberately choose to not formulate any hypothesis on green consumption values and consider our study to be explorative in this respect. Our two hypotheses on participants' attitudes therefore are:

H4.1: Higher values on the privacy concern scale are associated with lower acceptance values.

H4.2: A higher risk propensity is associated with higher acceptance values.

2.3.5 Demographics

In terms of demographics, we investigate hypotheses on age, gender, and education. Goldfarb and Tucker (2012) find that older people are less willing to provide information on their own income in an online survey compared to younger people. Andone et al. (2016) investigate the smartphone usage behavior of different age groups based on tracking a sample of more than 30,000 participants for at least 28 days. Their results show that younger people use their smartphones more time intensively and with a larger number of specialized apps than older people. Based on this literature, we assume that younger participants are more open towards the app scenarios described in our survey and therefore indicate higher acceptance values. In an experiment on the willingness to disclose different types of personal information in exchange for money, Benndorf and Normann (2018) find that female participants mostly request significantly more money than male participants. Research on privacy preferences in social networks shows that while women and men share similar amounts of information privately with friends, men are significantly more willing to share information publicly (Quercia et al., 2012). For our study, we therefore expect men to indicate higher acceptance values for data sharing in the scenarios described. In a national phone survey, Turow et al. (2005) examine the knowledge of 1,500 US Americans regarding data collection and data usage practices of commercial websites. The results show that the number of correctly answered questions was higher for participants with higher formal education. In this study, we therefore assume that participants with a higher formal education have more knowledge about data protection on the internet and, hence, are more skeptical about the scenarios described. Our hypotheses on participants' demographic attitudes are:

H5.1: A higher age is associated with lower acceptance values.
H5.2: Male participants have higher acceptance values.
H5.3: A higher formal education is associated with lower acceptance values.

2.4 Power analysis

In order to get an impression of the effect sizes at which we can detect significant treatment differences, we conducted a power analysis. For the power analysis, we estimated a mean value for the information attribute *live location* as an example, since a similar attribute ("its owners location") is also included in the study by Apthorpe et al. (2018). The authors use an acceptance scale that ranges from -1.5 to 1.5. In their study, the acceptance values for "its owners location" range from -0.67 to -0.28 with a mean value of -0.43 for various IoT senders. Transferred to our acceptance scale, which ranges from -1 to 1, this corresponds to an acceptance value of -0.29. However, since in all of our scenarios more attributes are transmitted than in the scenarios of Apthorpe et al. (2018), and since the senders in our scenarios are not IoT devices but actors from the private or public sector, we expect a slightly lower acceptance value, which we assume to be -0.4. Since no standard deviations are reported in Apthorpe et al. (2018), we assume a standard deviation of 0.5. In line with our hypothesis, we expect higher acceptance values in T2. Based on the power analysis, we estimate the minimum distance between the mean acceptance values that is required to obtain a significant result by using a two sample (one-sided) means test. Since we perform 30 (21) pairwise tests on hypothesis H1.1 (H1.2), there is a high probability for the occurrence of Type I errors. We therefore choose a low significance level of $alpha = 0.005$. For a significance level of $alpha\ =\ 0.005$, a power of 0.8, and a standard deviation of 0.5, the distance would have to be 0.107 (or 0.214 standard deviations) when considering a single scenario with an average participant number of $n = 506$ per treatment. We consider this calculated necessary effect size between the means of the two treatments to be large enough to indicate meaningful treatment effects.

2.5 Procedures

Our online survey was programmed with the software LimeSurvey. Before the survey was dispatched to participants, a pre-test for comprehensibility and length was conducted with six university researchers. In addition, we used the pre-test for a qualitative check of our scenarios in terms of the validation criteria of internal consistency, plausibility, creativity, and relevance (Amer et al., 2013). As a result, we refined the wording in some scenarios and included additional recipients.

The recruiting of the participants was conducted by a panel provider in September 2020. The participant sample is representative for the German population between 18 and 69 years in terms of gender, age, federal state, and education (see Appendix B). The respondents' payment (50 cents per participant) was also processed via the panel provider. The email announced a “survey on digital technologies” to avoid a link to privacy (or data protection) research.

A total of 1,357 people participated in the survey. 10.61% ($N = 144$) of the respondents did not complete the questionnaire. Among the persons who answered the questionnaire completely, 14.01% ($N = 170$) did not pass the quality check question[7]. Accordingly, the sample size reduced to 1,043. In a second step, we identified and eliminated speeders. The

[7] The quality check question was integrated as one item in the GREEN consumption scale. The wording of the question was: “To make sure that you read the questionnaire carefully, please select the answer option ‘strongly agree (7)’.”

median time to complete the questionnaire was 9:30 minutes. Participants ($N = 23$) requiring less than 1/3 of the interview time (3:10 minutes) were dropped. In a last step, seven people were removed after a manual quality check.[8] The final sample included 1,013 participants with a female share of 51.73% ($N = 524$) and an average age of 45.81 years ($sd = 14.42$).

3. Results

This section presents the results of our survey. In section 3.1, the acceptance values for each scenario are presented and possible treatment effects are examined. We deliberately avoid comparing acceptance values for identical recipients and information attributes in different scenarios since the different scenarios describe various sending device and provider combinations as well as varying mandatory data specifications and transmission benefits. Thereafter, we examine to what extent the acceptance values within the scenarios differ between recipients (section 3.2) and information attributes (section 3.3). Based on a regression analysis, we further investigate how the response behavior of our participants is influenced by their attitudes as well as their demographic characteristics (section 3.4).

3.1 Acceptance values and treatment effects

Tables 2 and 3 show the average acceptance values for optional recipients and optional information attributes in each scenario and for both treatments. Overall, in both tables, not a single acceptance value is greater than zero and therefore all values are in the unacceptable range. In Table 2 (recipients), the acceptance values range from -0.79 to -0.18. Similarly, in Table 3 (information attributes), the acceptance values range from -0.80 to -0.18. As depicted in the histograms in Appendix C, the relatively low average acceptance values can be explained by the fact that for each question a large number of participants chose the answer with the lowest value ("completely unacceptable"). A total of 10.86% ($N = 110$) chose this answer for each individual question in the scenarios A to E. In Tables 2 and 3, we do not observe a significant treatment effect for any of the different recipients and information attributes (pairwise comparisons with two-sample Wilcoxon rank-sum tests; all $p - values > 0.005$). In addition, there are no indications that acceptance values in one treatment are systematically higher or lower than in the other treatment. We thus reject hypotheses H1.1 and H1.2.

[8] These participants showed no variance in their responses regarding the GREEN consumption scale and the privacy concerns scale, although reverse items were included. For these items, the respective participants always chose the answer option (7) "strongly agree", so that the quality check was randomly passed.

Scenario	A		B		C		D		E			
Sending device and provider	Loyalty card with app from supermarket chains		Tracking bracelet with app from a health insurance company		Nutrition app from the Federal Ministry of Health		Mobility tracking app from a start-up company		Smart meter with app from an energy provider		Average acceptance values	
Recipient	T1	T2	T1	T2	T1	T2	T1	T2	T1	T2	T1	T2
Household members	-.20 (.70)	-.21 (.70)	-.29 (.71)	-.34 (.69)	-.38 (.68)	-.42 (.68)	-.39 (.68)	-.42 (.68)	-.21 (.72)	-.20 (.71)	-.29 (.60)	-.32 (.58)
Employer	-.66 (.55)	-.68 (.56)	-.69 (.52)	-.71 (.53)	-.74 (.47)	-.76 (.47)	-.76 (.47)	-.77 (.46)	-.79 (0.42)	-.78 (.45)	-.73 (.43)	-.74 (.44)
Federal ministries	-.36 (.66)	-.42 (.62)	-.44 (.63)	-.47 (.63)	-	-	-.52 (.60)	-.53 (.61)	-.51 (.60)	-.51 (.60)	-.46 (.53)	-.48 (.54)
City or municipality	-	-	-	-	-	-	-.60 (.56)	-.57 (0.60)	-.51 (.59)	-.47 (.61)	-.55 (.52)	-.52 (.55)
Market research comp.	-.18 (.67)	-.19 (.66)	-.38 (.65)	-.39 (.65)	-.44 (.62)	-.43 (.65)	-	-	-	-	-.33 (.58)	-.34 (.58)
German food prod.	-.26 (.65)	-.26 (.66)	-	-	-.55 (.57)	-.49 (.63)	-	-	-	-	-.40 (.55)	-.37 (.58
American food prod.	-.65 (.52)	-.63 (.54)	-	-	-	-	-	-	-	-	-.65 (.52)	-.63 (.54)
Chinese food prod.	-.69 (.51)	-.70 (.51)	-	-	-	-	-	-	-	-	-0.69 (0.51)	-0.70 (0.51)
German sports equip. prod.	-	-	-.53 (.60)	-.54 (.60)	-	-	-	-	-	-	-.53 (.60)	-.54 (.60)
German elect. prod.	-	-	-	-	-	-	-	-	-.51 (.60)	-.48 (.61)	-.51 (.60)	-.48 (.61)
Health insurance company	-.48 (.63)	-.48 (.65)	-	-	-	-	-	-	-	-	-.48 (.63)	-.48 (.65)
Car insurance company	-	-	-	-	-	-	-.65 (.52)	-.67 (.53)	-	-	-.65 (.52)	-.67 (.53)
Public transport companies	-	-	-	-	-	-	-.51 (.61)	-.52 (.62)	-	-	-.51 (.61)	-.52 (.62)
German Society for Nutrition	-	-	-	-	-.41 (.64)	-.40 (.66)	-	-	-	-	-0.41 (0.64)	-0.40 (0.66)
Neighbors	-	-	-	-	-	-	-	-	-.78 (.42)	-.78 (.45)	-.78 (.42)	-.78 (.45)
Average acceptance values	-.44 (.47)	-.45 (.49)	-.47 (.52)	-.49 (.52)	-.50 (.51)	-.50 (.53)	-.57 (.48)	-.58 (.48)	-.55 (.44)	-.54 (.46)		
$n =$	505	508	505	508	505	508	505	508	505	508	505	508

Average acceptance values: Color division					
	-1 to -0.8	> -0.8 to -0.6	> -0.6 to -0.4	> -0.4 to -0.2	> -0.2 to 0
	> 0 to 0.2	> 0.2 to 0.4	> 0.4 to 0.6	> 0.6 to 0.8	> 0.8 to 1

Table 2: Mean acceptance values for different data recipients in scenarios A to E.

Note: The row ‘average acceptance values’ refers to the average acceptance value for all recipients included in the respective scenario. The column ‘average acceptance values’ refers to the average acceptance value for all scenarios where the respective recipient is included. Acceptance values for specific recipients are never significantly different between T1 and T2 when assuming a significance level of $p < 0.005$ (two-sample Wilcoxon rank-sum test). Even at a higher significance level of $p < 0.05$, none of the differences is significant.

Scenario	A		B		C		D		E			
Sending device and provider	Loyalty card with app from supermarket chains		Tracking bracelet with app from a health insurance company		Nutrition app from the Federal Ministry of Health		Mobility tracking app from a start-up company		Smart meter with app from an energy provider		Average acceptance values	
Attribute	T1	T2	T1	T2	T1	T2	T1	T2	T1	T2	T1	T2
Live location	-.60 (.56)	-.60 (.56)	-.61 (.57)	-.62 (.56)	-.68 (.52)	-.70 (.51)	-	-	-.67 (.54)	-.71 (.51)	-.64 (.49)	-.66 (.47)
Monthly net income	-	-	-	-	-.73 (.48)	-.75 (.49)	-.76 (.46)	-.77 (.45)	-.75 (.47)	-.80 (.43)	-.75 (.44)	-.78 (.42)
Nutrition style	-.29 (.66)	-.21 (.69)	-.37 (.68)	-.33 (.69)	-	-	-	-	-	-	-.33 (.62)	-.27 (.63)
Food intol. and allergies	-.25 (.67)	-.18 (.72)	-	-	-.34 (.69)	-.32 (.72)	-	-	-	-	-.30 (.62)	-.25 (.65)
Body weight and height	-.53 (.59)	-.48 (.62)	-.37 (.67)	-.36 (.69)	-	-	-	-	-	-	-.45 (.57)	-.42 (.60)
Member-ships in a sports club or gym	-	-	-.44 (.64)	-.43 (.66)	-.52 (.60)	-.53 (.62)	-	-	-	-	-.48 (.59)	-.48 (.60)
Profession	-	-	-	-	-	-	-.55 (.59)	-.55 (.61)	-.64 (.54)	-.65 (.56)	-.60 (.52)	-.60 (.55)
Number of steps taken	-.45 (.62)	-.43 (.65)	-	-	-	-	-	-	-	-	-.45 (.62)	-.43 (.65)
Date of birth	-	-	-	-	-	-	-.40 (.65)	-.41 (.66)	-	-	-.40 (.65)	-.41 (.66)
Driving behavior	-	-	-	-	-	-	-.49 (.61)	-.50 (.63)	-	-	-.49 (.61)	-.50 (.63)
Time and duration of use of indi. power sources	-	-	-	-	-	-	-	-	-.26 (.68)	-.25 (.69)	-.26 (.68)	-.25 (.69)
Average acceptance values	-.42 (.51)	-.38 (.53)	-.45 (.56)	-.43 (.56)	-.57 (.49)	-.58 (.49)	-.55 (.50)	-.56 (.50)	-.58 (.45)	-.60 (.43		
$n =$	505	508	505	508	505	508	505	508	505	508	505	508

Average acceptance values: Color division	-1.0 to -.8	> -.8 to .6	> -.6 to -.4	> -.4 to -.2	> -.2 to 0.0
	> 0.0 to .2	> .2 to .4	> .4 to .6	> .6 to .8	> .8 to 1.0

Table 3: Mean acceptance values for different information attributes in scenarios A to E.
Note: The row ‘average acceptance values’ refers to the average acceptance value for all information attributes included in the respective scenario. The column ‘average acceptance values’ refers to the average acceptance value for all scenarios where the respective information attribute is included. Acceptance values for specific information attributes are never significantly different between T1 and T2 when assuming a significance level of $p < 0.005$ (two-sample Wilcoxon rank-sum test). Even at a higher significance level of $p < 0.05$, none of the differences is significant.

3.2 Acceptance towards data sharing with optional data recipients

In this section, differences in the acceptance towards data sharing with optional recipients are investigated for each scenario. For space reasons, we will not discuss each individual result in detail. Instead, we focus on results that are related to the hypotheses H2.1 and H2.2. We use non-parametric Wilcoxon signed-rank tests (matched samples) to examine whether acceptance values differ between optional data recipients.[9] Since we do not find any treatment effects and our hypotheses on optional recipients do not refer to individual treatments, we use pooled data for the pairwise tests. The results for all pairwise tests can be found in Appendix D, Tables 11 to 15.

As Table 2 shows, comparatively high acceptance values can be observed for *household members* (ranging from -0.42 in scenarios C and D to -0.20 in scenario A) while *employers* belong to the recipients with the lowest acceptance values across all scenarios (ranging from -0.79 in scenario E to -0.66 in scenario A). In all scenarios the acceptance values for data sharing with *household members* are almost always significantly higher than for other recipients (Wilcoxon signed rank tests, $p-values < 0.01$). In scenario A (Appendix D, Table 11), however, there is no significant difference between *household members* and *market research companies* ($p-value = 0.633$). In scenario C (Appendix D, Table 13), the difference is also not significant for *market research companies* ($p-value = 0.014$) and for the *German Society for Nutrition* ($p-value = 0.877$). Concerning data sharing with *employers*, the acceptance values are almost always significantly lower than for other recipients ($p-values < 0.01$), except for *American food producers* ($p-value = 0.306$) and *Chinese food producers* ($p-value = 0.067$) in scenario A (Appendix D, Table 11), and for *neighbors* ($p-value = 0.431$) in scenario E (Appendix D, Table 15). We thus find predominant support for hypotheses H2.1 and H2.2.

3.3 Acceptance towards data collection of optional information attributes

This section focuses on differences in the acceptance values for data collection of optional information attributes. In order to test hypotheses H3.1 and H3.2, we compare acceptance values from all scenarios which include the optional information attributes *life location* and *monthly net income*. Tables 16 to 20 in Appendix D show the results for all pairwise tests.

In accordance with hypotheses H3.1, we observe the lowest acceptance values for the information attributes *live location* (ranging from -0.71 in scenario E to -0.60 in scenario A, see

[9] In sections 3.2 and 3.3, we use non-parametric Wilcoxon signed-rank tests instead of parametric t-tests because the differences between the individual acceptance values are not normally distributed.

Table 3) and *monthly net income* (ranging from -0.80 in scenario E to -0.73 in scenario C). The acceptance values for *live location* are significantly lower than the acceptance values for all other information attributes in scenario A and B (Appendix D, Tables 16 and 17, all $p-values < 0.001$). Likewise, the acceptance values for *monthly net income* are significantly lower than the acceptance values for all other information attributes in scenarios C, D, and E (Appendix D, Tables 18, 19 and 20, all $p-values < 0.001$). Therefore, we accept hypothesis H3.1. In scenarios C and E, the acceptance values for *monthly net income* are significantly lower than for *live location* (both $p-values < 0.001$). We thus, reject hypothesis H3.2.

3.4 The influence of personal attitudes and demographics

In this section, we use random-effects generalized least squares (GLS) regression models to test our hypotheses on attitudes and demographics. In Table 4, the dependent variable is either the acceptance value indicated for each data recipient (models 1-4) or for each information attribute (models 5-8). Since each participant indicated a total of 30 acceptance values for data recipients and a total of 21 acceptance values for information attributes, the number of observations in Table 4 is $1{,}013 * 30 = 30{,}390$ in models 1-4 and $1{,}013 * 21 = 21{,}273$ in models 5-8.

The upper three independent variables in Table 4 are related to participants' personal attitudes. *Privacy* and *GREEN* are scores calculated from the average answer values to the privacy concern scale of Ham (2017) and the GREEN scale of Haws et al. (2014). For the privacy scale, we obtain a Cronbach's alpha of 0.69 and for the GREEN scale a Cronbach's alpha of 0.71. Mean values and standard deviations for each item of these scales can be found in Appendix E (Tables 21 and 23). The variable *Risk* contains the indicated risk propensity of the participants based on Dohmen et al. (2011) where a higher number indicates a higher willingness to take risks. The mean value and standard deviation for this question can be found in Appendix E (Table 22). *Education (high)* and *Education (low)* are dummy variables that take a value of 1 if the participant has a high school degree, or a degree from a basic secondary school or lower.[10]

Models 1 and 5 analyze the influence of participants' online privacy concerns, risk propensity, and green consumption values on the acceptance towards data sharing (model 1) and data collection (model 5). In models 2 and 6, we focus on the influence of demographic variables. In models 3 and 7, we consider both personal attitudes and demographic characteristics. Since previous research by Dohmen et al. (2011, 2017) shows that risk attitudes are higher for younger people and for men, we include the interaction terms *Risk*Age* and *Risk*Male* in

[10] The variable Education (medium) is omitted.

models 4 and 8. The results of the studies by Fast and Schnurr (2020) and Fogel and Nehmad (2009) further show that women, on average, have higher privacy concerns than men. We therefore include the interaction term *Privacy*Male* in models 4 and 8. All regression models contain control dummies for optional recipients (models 1-4) or for optional information attributes (models 5-8).

	Dep. var. acceptance values for optional							
	data recipients				**information attributes**			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Privacy	-0.17***		-0.16***	-0.12***	-0.17***		-0.17***	-0.13***
	(0.01)		(0.01)	(0.02)	(0.01)		(0.01)	(0.02)
Risk	0.02***		0.01*	0.04*	0.02***		0.01*	0.03
	(0.01)		(0.01)	(0.02)	(0.01)		(0.01)	(0.02)
GREEN	0.03*		0.04**	0.03**	0.03*		0.04**	0.04**
	(0.01)		(0.01)	(0.01)	(0.01)		(0.01)	(0.01)
Age		-0.01***	-0.01***	-0.00		-0.01***	-0.01***	-0.00
		(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)
Gender (Male=1)		0.05	0.02	0.29*		0.06*	0.03	0.34*
		(0.03)	(0.03)	(0.13)		(0.03)	(0.03)	(0.14)
Education (high)		-0.10**	-0.09**	-0.09**		-0.06	-0.05	-0.05
		(0.03)	(0.03)	(0.03)		(0.03)	(0.03)	(0.03)
Education (low)		0.00	-0.01	-0.01		-0.01	-0.02	-0.03
		(0.03)	(0.03)	(0.03)		(0.03)	(0.03)	(0.03)
Risk*Age				-0.00**				-0.00*
				(0.00)				(0.00)
Risk*Male				0.03**				0.03**
				(0.01)				(0.01)
Privacy*Male				-0.08**				-0.08***
				(0.02)				(0.02)
Treatment (T2=1)	0.00	-0.01	0.00	0.01	0.02	0.01	0.02	0.02
	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)
Constant	0.13	-0.13*	0.46***	0.06	0.00	-0.32***	0.31**	-0.06
	(0.09)	(0.06)	(0.10)	(0.14)	(0.09)	(0.06)	(0.10)	(0.15)
Controls for optional recipients / optional information attributes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	30390	30390	30390	30390	21273	21273	21273	21273
N (groups)	1013	1013	1013	1013	1013	1013	1013	1013
Wald Chi^2	5234.68	5100.38	5311.24	5349.44	3813.26	3652.12	3872.95	3905.44

Table 4: Random-effects GLS regression of acceptance towards data sharing with optional recipients (models 1-4) or of acceptance towards data collection of optional information attributes (models 5-8) on participants' attitudes, demographic characteristics, and treatment. Standard errors in parentheses: $^{*}\ p < 0.01$, $^{**}\ p < 0.005$, $^{***}\ p < 0.001$.

Our results show significant negative effects for the variable *Privacy*. Stronger preferences for privacy have a large negative effect on the acceptance towards data sharing and on the acceptance towards data collection. This result is not surprising since the dependent variables in Table 4 and the privacy variable measure, in a broad sense, similar outcomes. Therefore, we accept hypothesis H4.1. In line with hypothesis H4.2, *Risk* has a significant positive effect on the dependent variable except for model 8. This suggests that risk takers are, on average, less reluctant to disclose their personal information. We did not formulate a hypothesis for a possible effect of the *GREEN* scale due to a lack of appropriate literature. In all models that include the GREEN scale, a higher value on the *GREEN* scale has a significant positive effect on the dependent variable. This implies that participants with a higher value on the *GREEN* scale are, on average, more open to disclose their personal information

For the demographic variables, we observe a significant negative effect of the variable *Age* in models 2, 3, 6, and 7. In models 4 and 8, *Age* is no longer significant, but the interaction term of the variables *Age* and *Risk* is significant and negative. The interaction term indicates that the significant negative effect of Age is mainly driven by the higher risk aversion of older participants. Thus, we find predominant support for hypothesis H5.1. The variable *Male* has a significant positive effect in models 4, 6, and 8. We therefore accept hypothesis H5.2. The interaction terms *Risk*Male* and *Privacy*Male* suggest that the effects of a stronger risk propensity and of stronger privacy concerns on the dependent variables significantly differ between women and men. For men, a higher value on the risk propensity (privacy concern) scale is associated with significantly higher (lower) acceptance values. In models 2, 3, and 4, *Education (high)* has a significant negative effect on the dependent variable. We do not observe significant effects of this variable for models 5 to 8 where the acceptance towards the collection of optional information attributes is the dependent variable. However, since the sign of *Education (high)* is also negative in models 5 to 8, we accept hypothesis H5.3.

4. Discussion and limitations

The results from Tables 2 and 3 show that our two different treatments do not lead to significant differences in the average acceptance values for the same recipients or information attributes. In addition, no clear trend can be identified.

The treatments in our scenarios differed only in one sentence, which emphasized different transmission benefits at the end of each scenario. Therefore, a possible explanation for the non-existent or only minor treatment effects is that the emphasized transmission benefits between the two treatments did not differ sufficiently. It is also possible that some of the participants interpreted the environmental benefits highlighted in T2 as not trustworthy. The results of a study conducted with Portuguese students by Do Paço and Reis (2012), show that students with particularly strong environmental concerns tended to be particularly skeptical about environmentally friendly advertising messages from companies. The mean across all items of the GREEN scale suggests that participants in our survey have comparatively strong environmental concerns. In Haws et al. (2014), the mean of the GREEN scale is 3.95, whereas for our participants it is significantly higher with 4.71. It is likely that participants in T2 in our survey were skeptical about the highlighted environmental benefits of the app and that these benefits therefore had no effect on the indicated acceptance values. In a study on greenwashing (i.e., deceptive advertising about the environmental characteristics of goods), Schmuck et al. (2018) find that the negative effect of perceived greenwashing statements can be outweighed by nature images presented together with the greenwashing statements. It is thus also possible that a more detailed description or a visual presentation of the respective transmission benefits in our survey would have resulted in more pronounced treatment effects. A further explanation for the lack of treatment effects is that the acceptance decisions queried in the scenarios were simply less influenced by the transmission benefits but more by the perceived threats of data sharing.

The average acceptance values of the individual scenarios in our survey are not directly comparable since the scenarios differ in several parameters. Nevertheless, in each scenario, special care was taken to include both relatively uncritical as well as sensitive recipients and information attributes. The results show that the acceptance values are highest in the app scenarios that are probably relatively familiar to the participants. As explained in section 2.1.1, apps similar to those in scenario A (loyalty card) and B (tracking bracelet) also have a significantly higher market penetration than apps similar to those in scenario D (mobility tracking) or E (smart meter). Smart meters will be mandatory in all German households by the year 2032. Therefore, energy providers and relevant public authorities can use the low acceptance values in scenario E (smart meter) as an indication that broad-based information campaigns may be necessary to increase acceptance of this technology.

In general, we observe that the comparatively highest acceptance values were indicated for information attributes that show a close thematic fit with the respective scenario. For example, comparatively high acceptance values were indicated for *nutrition style* and *food intolerances and allergies* in scenario A (loyalty card). It is quite plausible that data on these information attributes can be used to make the personalized product recommendations described in scenario A as accurate as possible. This is not the case for the information attributes *body weight and height* and *number of steps taken*, which have significantly lower acceptance values. Another example can be found in scenario E (smart meter). Here, the acceptance value for the information attribute *time and duration of use of the individual power sources* is significantly higher than for *profession*.

In our regression analysis (Table 4), we found a significant positive effect of the GREEN scale on the acceptance values. One explanation for this effect could be that participants with higher values on the GREEN scale assume that they behave in accordance with existing social norms on environmental aspects. Those participants may be less concerned that the disclosure of personal information may have negative consequences for them and therefore chose higher acceptance values in our survey.

One limitation of this study lies in the selection of the participants. Although the respondents were selected according to quotas for gender, age, federal state, and education, it can be assumed that the participants of our survey do not fully represent the German population. Since our study was conducted via a professional panel provider and with comparatively low monetary incentives, it is likely that our participants have an above-average internet affinity and intrinsic motivation. This assumption is further supported by the fact that participants accepted the invitation for an online survey on digital technologies.

A second limitation is that our study did not evaluate actual data sharing behavior. It is quite likely that in reality, participants of our survey would share personal data without much concern, even though they indicated low levels of acceptance in our survey. In economic experiments, in which participants decide on actual payoff relevant actions, it is often the case that participants show a comparatively open data transfer behavior, although they previously stated strong privacy preferences (Kokolakis, 2017; Norberg et al., 2007). Therefore, our results cannot be used to draw direct conclusions about participants' actual data sharing behavior. However, there is no reason to assume that the differences between different recipients and information attributes and the effects of attitudes and demographic characteristics revealed in our results are not reflected in real world situations.

5. Conclusion and outlook

The aim of our study was to examine whether and how the acceptance regarding data sharing in smartphone apps from five different industries differs for several data recipients and information attributes. In two treatments, we further investigated whether acceptance values are higher when environmental (public) instead of monetary (private) data transmission benefits are highlighted. Results show no treatment effects for data sharing with different recipients and for collection of various information attributes.

Our results show statistically significant differences in acceptance values between almost all recipients and between almost all information attributes. Comparatively high acceptance values were identified for the recipients and information attributes that thematically corresponded with the respective scenario. In line with our hypotheses, comparatively high acceptance values were stated for the recipient *household members* while the lowest acceptance values were stated for *employers*. For the information attributes, our results revealed the lowest acceptance values for *live location* and *monthly net income*. The results from a regression analysis showed that the participants' age, a higher education level, and strong privacy concerns had a significant negative effect on acceptance values. In contrast, we found that participants with stronger GREEN consumption values, a higher willingness to take risks, and male participants had, on average, higher acceptance values.

For developers and providers of technologies that may raise privacy concerns among potential users, our study provides illustrative examples on how to investigate acceptance toward the technology in question. Future research could examine whether differences in the acceptance evaluation of data sharing in smartphone apps (or stationary digital applications) become apparent when there is a more intensive and/or visual emphasis of monetary (private) and environmental (public) data sharing benefits. Scholars could further investigate to what extent the general acceptance of new technologies, which could be measured, e.g., with the Technological Readiness Adoption Index (Ramírez-Correa and Rondán-Cataluña, 2020), is affected by the privacy preferences of potential technology adopters. Within institutional and health economics, scenario-based approaches similar to those in this study could be used to ex ante evaluate public acceptance toward planned policies. Future studies could further use scenario-based surveys to examine the effect of design changes on, e.g., employer review platforms (Cloos, forthcoming) or online marketplaces.

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Appendix A – Scenarios

In all scenarios answer options were: (1) Completely unacceptable; (2) Somewhat unacceptable; (3) Rather unacceptable; (4) Rather acceptable; (5) Somewhat acceptable; (6) Completely acceptable.

<table>
<tr><th colspan="2">Scenario A - Loyalty card with app from supermarket chains</th></tr>
<tr><td colspan="2">Various supermarket chains collect information about the food you buy with a free, shared loyalty card in combination with a cost-free app. Name, address, date of birth, and gender must be entered in the app. Based on this information, the app will provide you with product recommendations tailored to your shopping behavior.</td></tr>
<tr><th>T1</th><th>T2</th></tr>
<tr><td>The app also offers discount coupons, which help you to save money while shopping.</td><td>The supermarket chains emphasize that no advertising leaflets are printed for their app users, thus avoiding waste and protecting the environment.</td></tr>
<tr><th colspan="2">Recipients</th></tr>
<tr><td colspan="2">How acceptable is it to you that the information collected with the loyalty card, is passed on to the following recipients in addition to the supermarket chains? The data transmission is mentioned in the app’s general terms and conditions.</td></tr>
<tr><td colspan="2">1. Market research companies</td></tr>
<tr><td colspan="2">2. German food producers</td></tr>
<tr><td colspan="2">3. American food producers</td></tr>
<tr><td colspan="2">4. Chinese food producers</td></tr>
<tr><td colspan="2">5. Household members (close family members or roommates)</td></tr>
<tr><td colspan="2">6. Federal ministries (e.g., for health, economic affairs, environment, transport)</td></tr>
<tr><td colspan="2">7. Health insurance company</td></tr>
<tr><td colspan="2">8. Employer</td></tr>
<tr><th colspan="2">Information attributes</th></tr>
<tr><td colspan="2">How acceptable is it to you that the supermarket chains request or collect and store the following additional information from the app user(s) via the app if this is mentioned in the app's general terms and conditions?</td></tr>
<tr><td colspan="2">1. Live location</td></tr>
<tr><td colspan="2">2. Nutrition style (e.g., vegetarian/vegan/...)</td></tr>
<tr><td colspan="2">3. Number of steps taken</td></tr>
<tr><td colspan="2">4. Food intolerances and allergies</td></tr>
<tr><td colspan="2">5. Bodyweight and height</td></tr>
</table>

Table 5: Description of scenario A.

Scenario B - Tracking bracelet with app from a health insurance company	
Your health insurance company provides you with a cost-free fitness bracelet in combination with a cost-free app to collect information about your activity status. Your daily steps and your heart rate form your activity status and determined via the fitness bracelet and automatically stored in the app. **Name, date of birth, and gender** must be entered in the app. The collected information is passed on to your health insurance company. Based on this information, your health insurance company will determine a weekly number of steps to be reached.	
T1	**T2**
For each week in which you reach the determined number of steps, **you will receive a bonus of € 3.00.**	For each week in which you reach the determined number of steps, **your health insurance company will assume a tree sponsorship of € 3.00 for worldwide reforestation projects.**
Recipients	
How acceptable is it to you that the information collected with the app is passed on to the following recipients, in addition to the health insurance company? The data transmission is mentioned in the app's general terms and conditions.	
1. Market research companies	
2. Household members (close family members or roommates)	
3. Employer	
4. Federal ministries (e.g., for health, economic affairs, environment, transport)	
5. German sports equipment producers	
Information attributes	
How acceptable is it to you that the health insurance company requests and respectively collects and stores the following additional information from the app user(s) via the app if this is mentioned in the app's general terms and conditions?	
1. Live location	
2. Nutrition style (e.g., vegetarian/vegan/...)	
3. Membership in a sports club or gym	
4. Body weight and height	

Table 6: Description of scenario B.

<table>
<tr><th colspan="2">Scenario C – Nutrition app from the Federal Ministry of Health</th></tr>
<tr><td colspan="2">The Federal Ministry of Health offers a cost-free app to give you personalized nutritional recommendations. Name, date of birth, gender, body weight, height, and your nutritional style must be entered in the app. In addition, you have to provide information about your typical weekly purchases to the app by photographing the corresponding receipts at regular intervals. This information is passed on to the Federal Ministry of Health.</td></tr>
<tr><th>T1</th><th>T2</th></tr>
<tr><td>Based on this information, the app will provide you with personalized nutritional recommendations aimed at maximizing health-promoting nutrition.</td><td>Based on this information, the app provides you with personalized nutritional recommendations aimed at maximizing environmentally friendly nutrition.</td></tr>
<tr><th colspan="2">Recipients</th></tr>
<tr><td colspan="2">How acceptable is it to you that the information collected with the app is passed on to the following recipients, in addition to the Federal Ministry of Health? The data transmission is mentioned in the app’s general terms and conditions of the app.</td></tr>
<tr><td colspan="2">1. Market research companies</td></tr>
<tr><td colspan="2">2. German food producers</td></tr>
<tr><td colspan="2">3. Household members (close family members or roommates)</td></tr>
<tr><td colspan="2">4. Employer</td></tr>
<tr><td colspan="2">5. German Society for Nutrition (independent scientific society)</td></tr>
<tr><th colspan="2">Information attributes</th></tr>
<tr><td colspan="2">How acceptable is it to you that the Federal Ministry of Health requests, or collects and stores the following additional information from the app user(s) via the app, if this is mentioned in the app's general terms and conditions?</td></tr>
<tr><td colspan="2">1. Live location</td></tr>
<tr><td colspan="2">2. Food intolerances and allergies</td></tr>
<tr><td colspan="2">3. Membership in a sports club or gym</td></tr>
<tr><td colspan="2">4. Monthly net income</td></tr>
</table>

Table 7: Description of scenario C.

Scenario D - Mobility tracking app from a start-up company	
A German technology start-up company collects information about your mobility behavior via a cost-free tracking app. **Name, gender, live location, and type of vehicle** (assume you own a car) must be entered obligatorily for the app. The tracking app registers whether you travel by car, public transport, bicycle, or by foot. In addition, the app has information on the current location-based petrol, diesel and electricity prices, on the prices of public local and long-distance transport, and on the current traffic loads on roads and public transport.	
T1	**T2**
Based on this information, the app provides you with personalized recommendations **aimed at maximizing cost- and time-saving mobility behavior**.	Based on this information, the app provides you with personalized recommendations **aimed at maximizing environmentally friendly mobility behavior**.
Recipients	
How acceptable is it to you that the information collected with the app (except for live location data) is shared with the following recipients, in addition to the start-up company? The data transmission is mentioned in the app's general terms and conditions.	
1. Local and long-distance public transport companies	
2. City or municipality (residence)	
3. Household members (close family members or roommates)	
4. Employer	
5. Federal ministries (e.g., for health, economic affairs, environment, transport)	
6. Car insurance company	
Information attributes	
How acceptable is it to you that the start-up company requests, or collects and stores the following additional information from the app user via the tracking app, if this is mentioned in the app's general terms and conditions?	
1. Date of birth	
2. Driving behavior (when using the car as driver)	
3. Profession	
4. Monthly net income	

Table 8: Description of scenario D.

Scenario E – Smart meter with app from an energy provider	
In your apartment (or flat-sharing community, or house) a smart meter with connected measuring systems is installed. The smart meter is an intelligent digital electricity meter that records and stores your power consumption at any time and can send the stored data. The smart meter receives data from the connected measuring systems, which record the electricity consumption of individual power sources (e.g., tv, refrigerator, room lighting) in your apartment. Through an app of your energy provider, which receives data from your smart meter, information about your current and past electricity consumption is provided to you, clearly arranged by the power source. **Name**, **address, and date of birth** must be entered in the app.	
T1	**T2**
Based on this information, the app provides you with personalized recommendations **aimed at minimizing your electricity costs**.	Based on this information, the app provides you with personalized recommendations **aimed at maximizing environmentally friendly power usage**.
Recipients	
How acceptable is it to you that the information collected with the app is passed on to the following recipients, in addition to the energy provider? The data transmission is mentioned in the app's general terms and conditions.	
1. Local and long-distance public transport companies	
2. City or municipality (residence)	
3. Household members (close family members or roommates)	
4. Employer	
5. Neighbors	
6. Federal ministries (e.g., for health, economic affairs, environment, transport)	
Information attributes	
How acceptable is it to you that the energy provider requests and respectively collects and stores the following additional information of the app user(s) via the app if this is mentioned in the app's general terms and conditions?	
1. Live location	
2. Profession	
3. Monthly net income	
4. Time and duration of use of the individual power sources	

Table 9: Description of scenario E.

Appendix B - Demographics

Quote	Specification	N (%)
Gender	Male	489 (48.27)
	Female	524 (51.73)
Age	18-29	185 (18.26)
	30-39	178 (17.57)
	40-49	177 (17.47)
	50-59	262 (25.86)
	60-69	211 (20.83)
Education	Basic secondary schooling or lower	337 (33.27)
	Intermediate school certificate or equivalent	314 (31.00)
	High school graduation	362 (35.73)
Federal State	Baden Wurttemberg	132 (13.03)
	Bavaria	167 (16.49)
	Berlin	43 (4.24)
	Brandenburg	29 (2.86)
	Bremen	7 (0.69)
	Hamburg	23 (2.27)
	Hesse	77 (7.60)
	Lower Saxony	103 (10.17)
	Mecklenburg Western Pomerania	19 (1.88)
	Northrhine-Westphalia	215 (21.22)
	Rhineland-Palatinate	54 (5.33)
	Saarland	12 (1.18)
	Saxony	47 (4.64)
	Saxony-Anhalt	27 (2.67)
	Schleswig Holstein	35 (3.46)
	Thuringia	23 (2.27)

Table 10: Demographics of survey participants.

Appendix C – Histograms

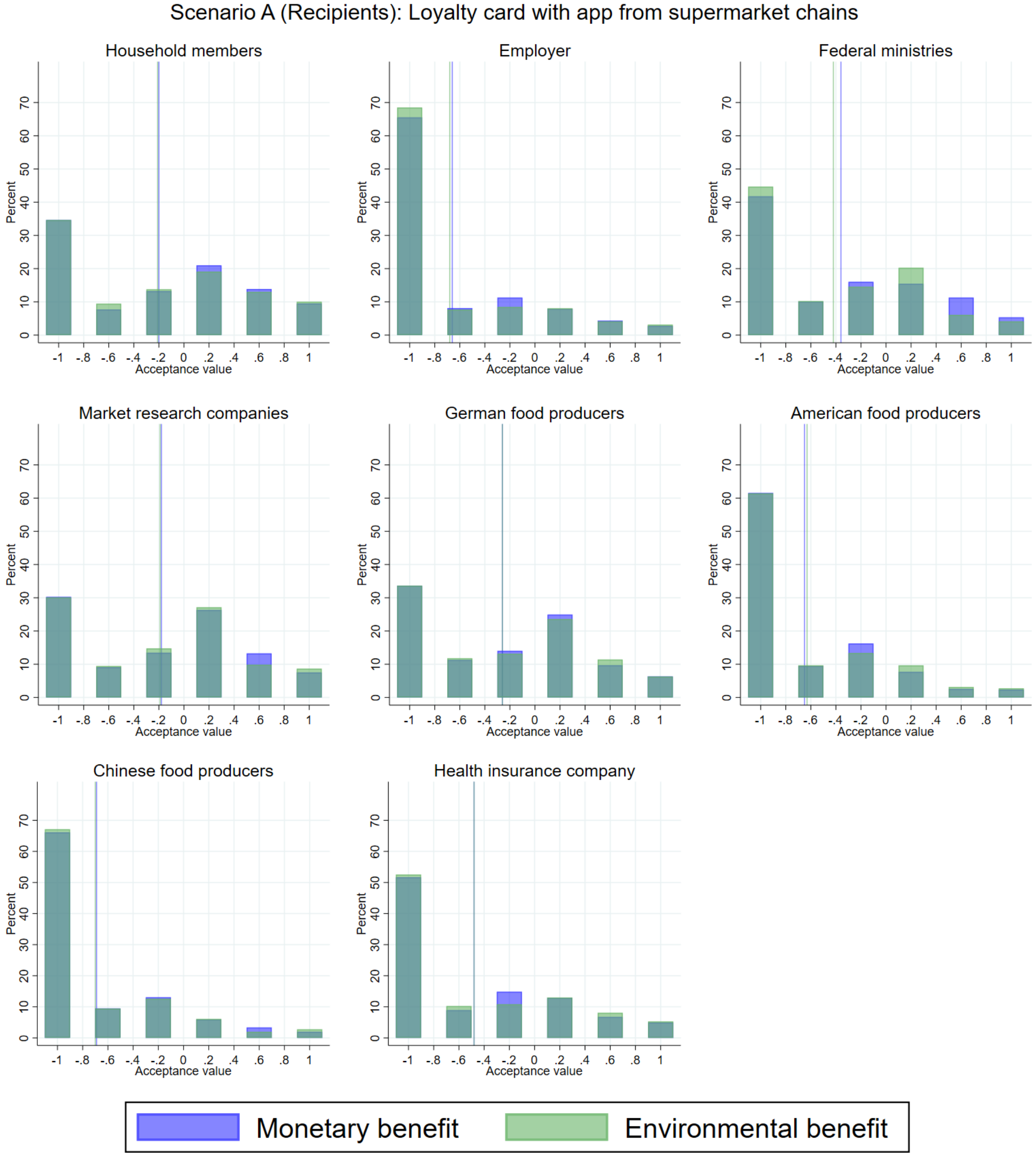

Figure 2: Histograms showing the percentage distribution of acceptance values for optional recipients in scenario A by treatment. Vertical lines indicate the mean values in T1 (blue) and T2 (green).

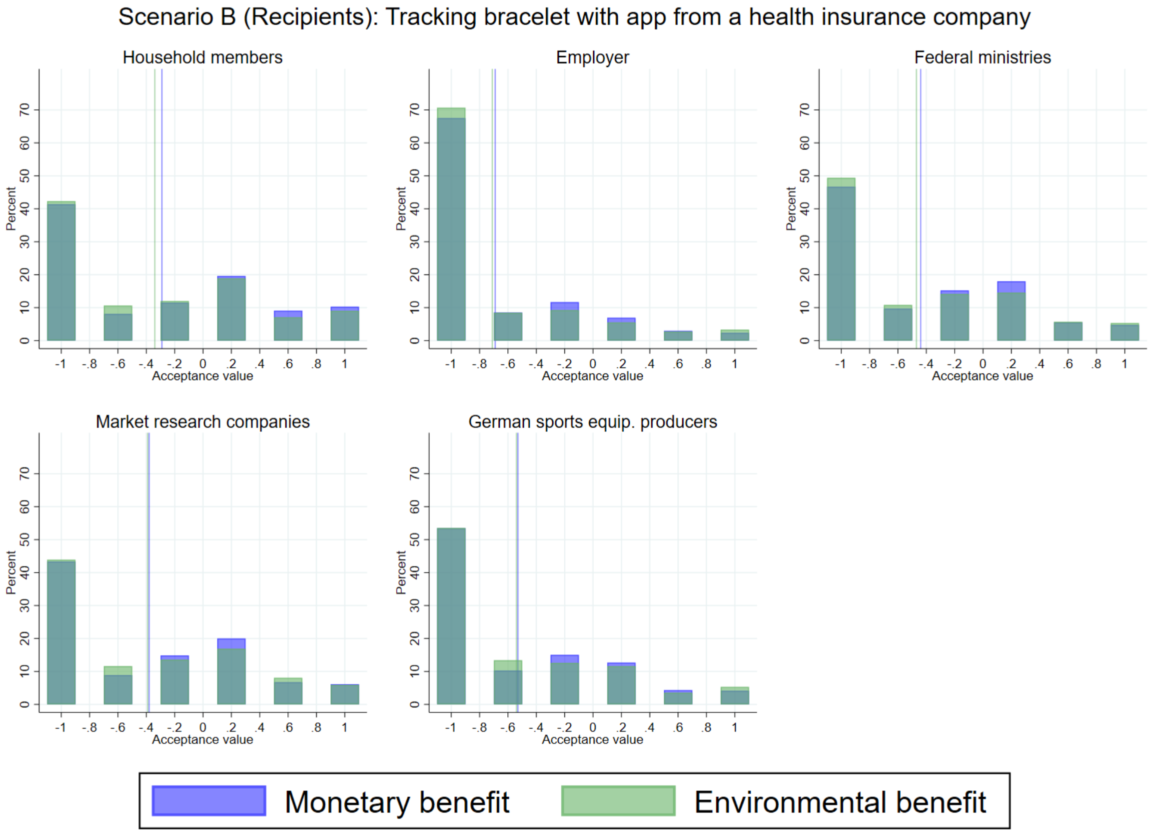

Figure 3: Histograms showing the percentage distribution of acceptance values for optional recipients in scenario B by treatment. Vertical lines indicate the mean values in T1 (blue) and T2 (green).

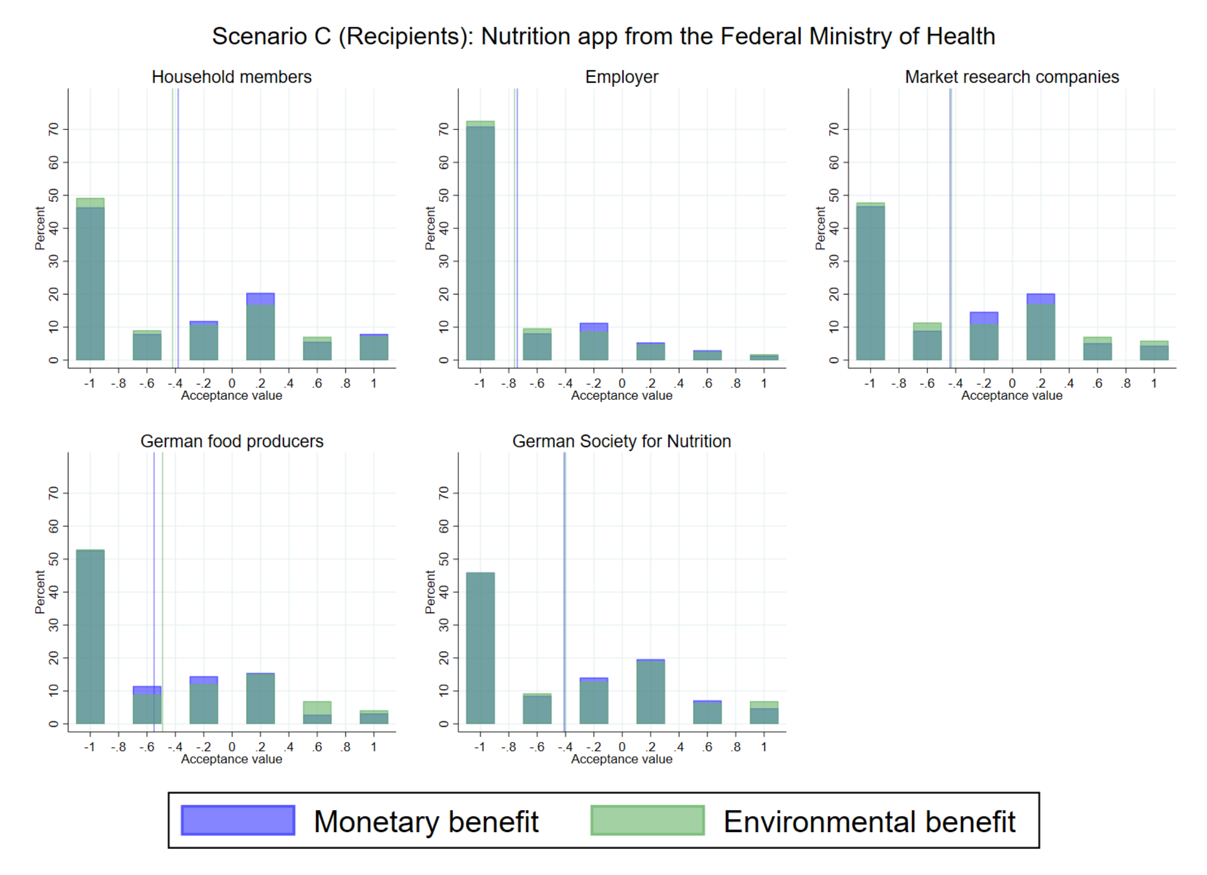

Figure 4: Histograms showing the percentage distribution of acceptance values for optional recipients in scenario C by treatment. Vertical lines indicate the mean values in T1 (blue) and T2 (green).

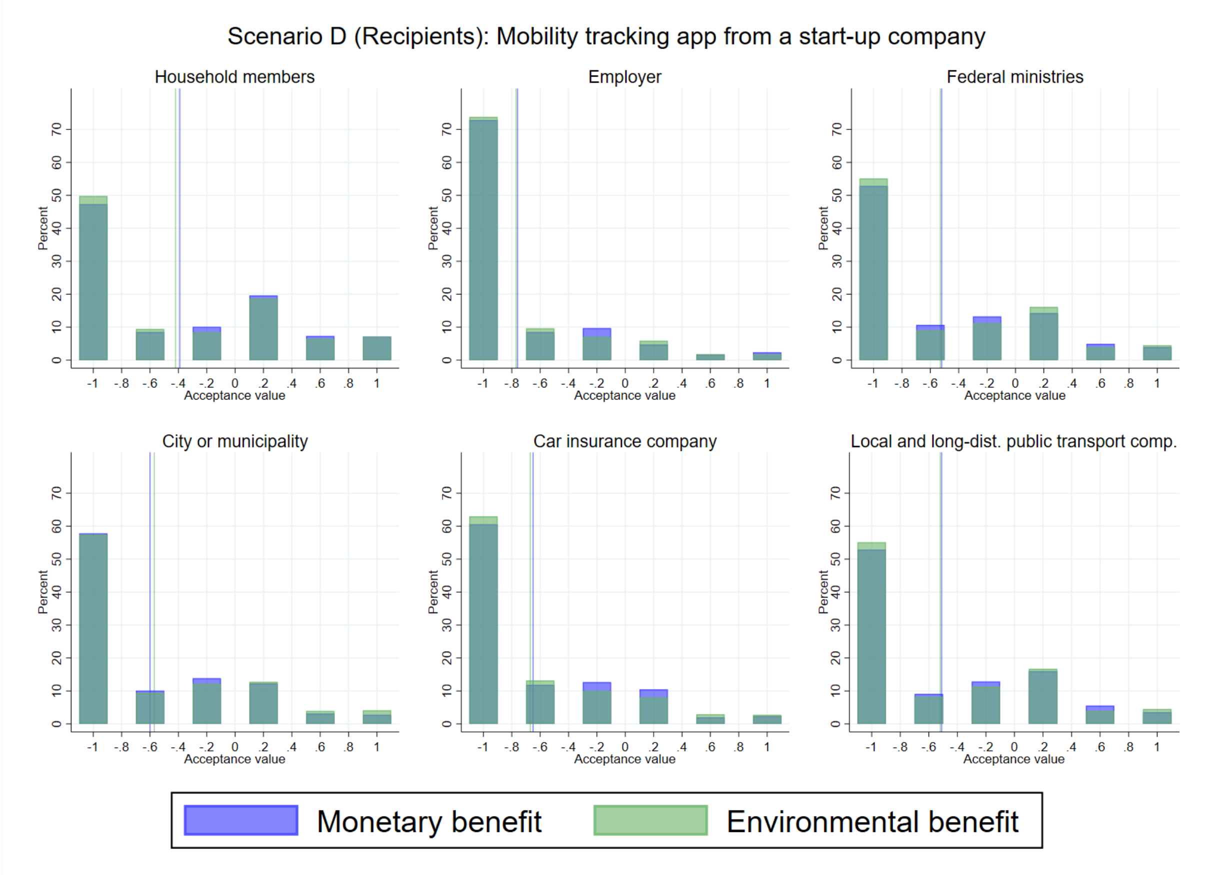

Figure 5: Histograms showing the percentage distribution of acceptance values for optional recipients in scenario D by treatment. Vertical lines indicate the mean values in T1 (blue) and T2 (green).

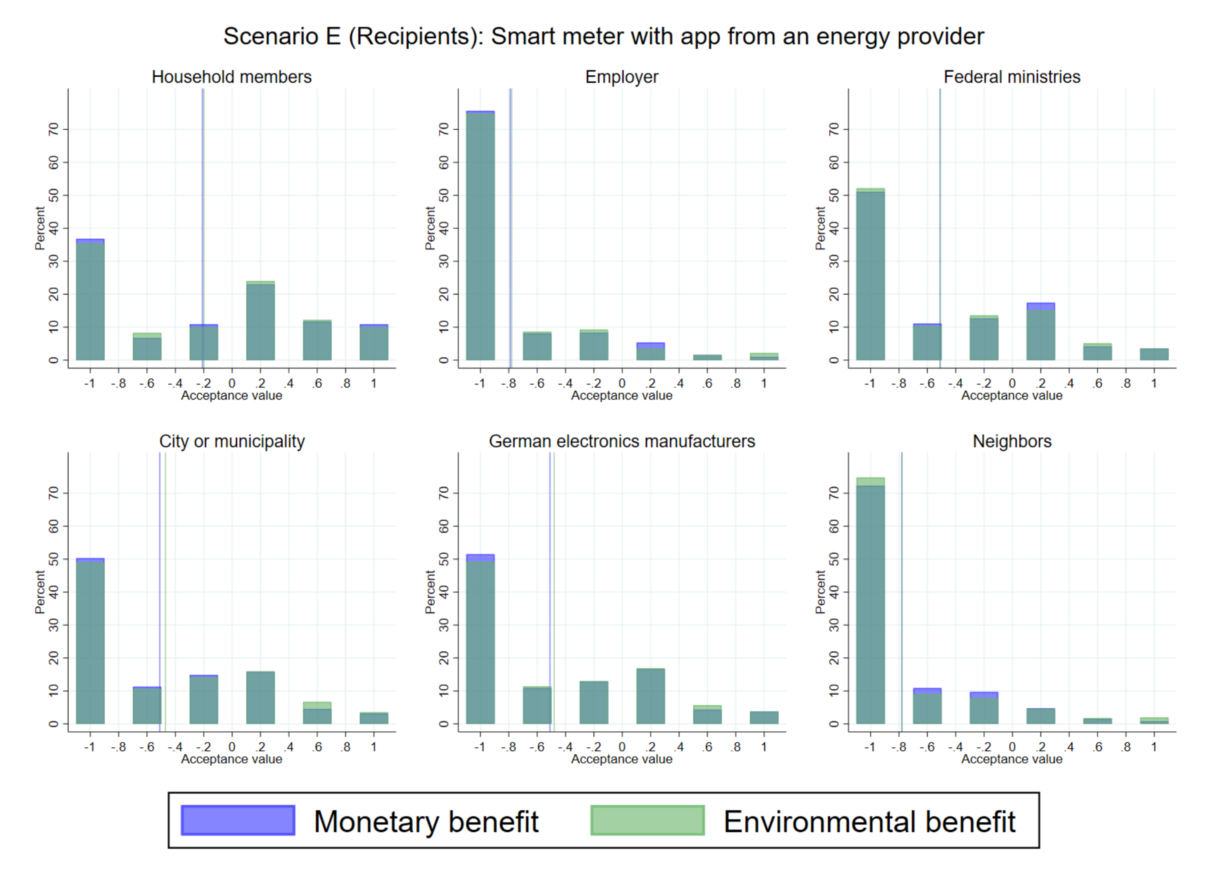

Figure 6: Histograms showing the percentage distribution of acceptance values for optional recipients in Scenario E by treatment. Vertical lines indicate the mean values in T1 (blue) and T2 (green).

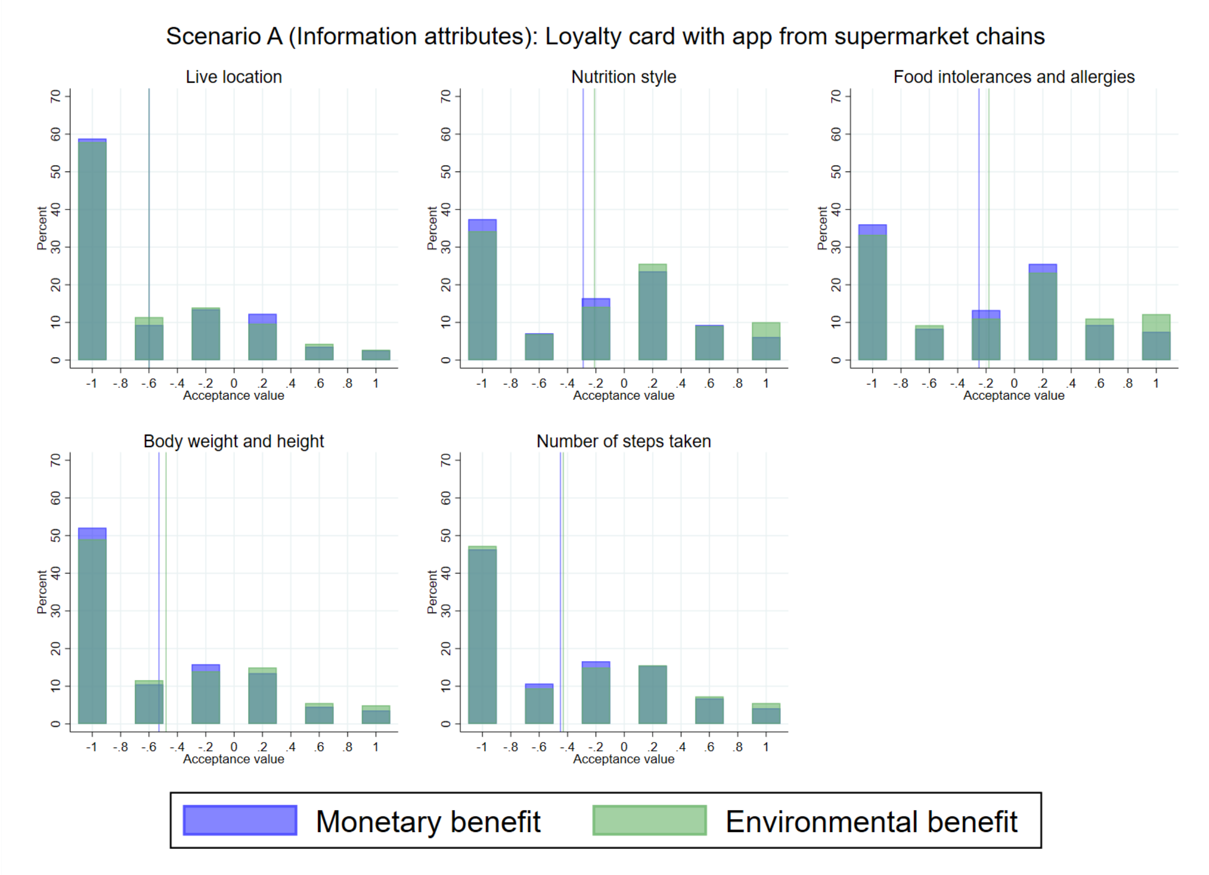

Figure 7: Histograms showing the percentage distribution of acceptance values for optional information attributes in scenario A by treatment. Vertical lines indicate the mean values in T1 (blue) and T2 (green).

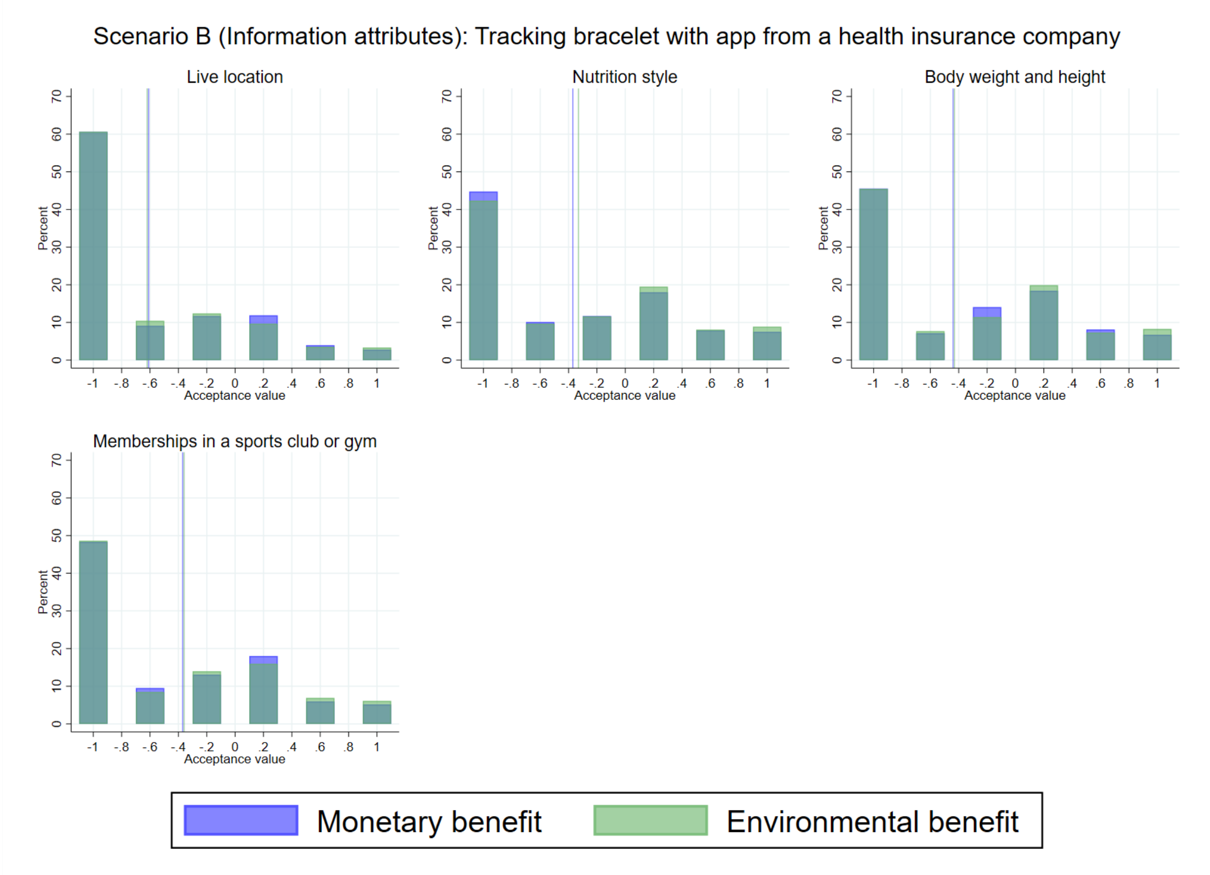

Figure 8: Histograms showing the percentage distribution of acceptance values for optional information attributes in scenario B by treatment. Vertical lines indicate the mean values in T1 (blue) and T2 (green).

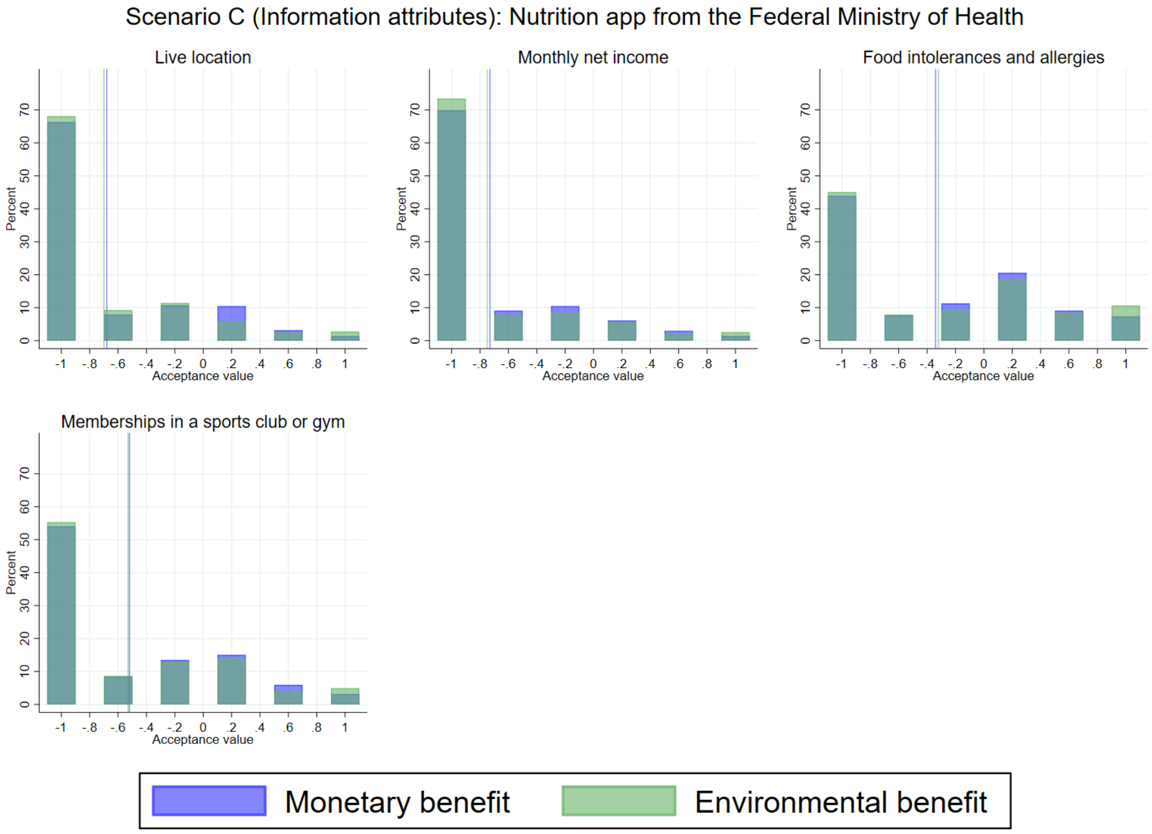

Figure 9: Histograms showing the percentage distribution of acceptance values for optional information attributes in scenario C by treatment. Vertical lines indicate the mean values in T1 (blue) and T2 (green).

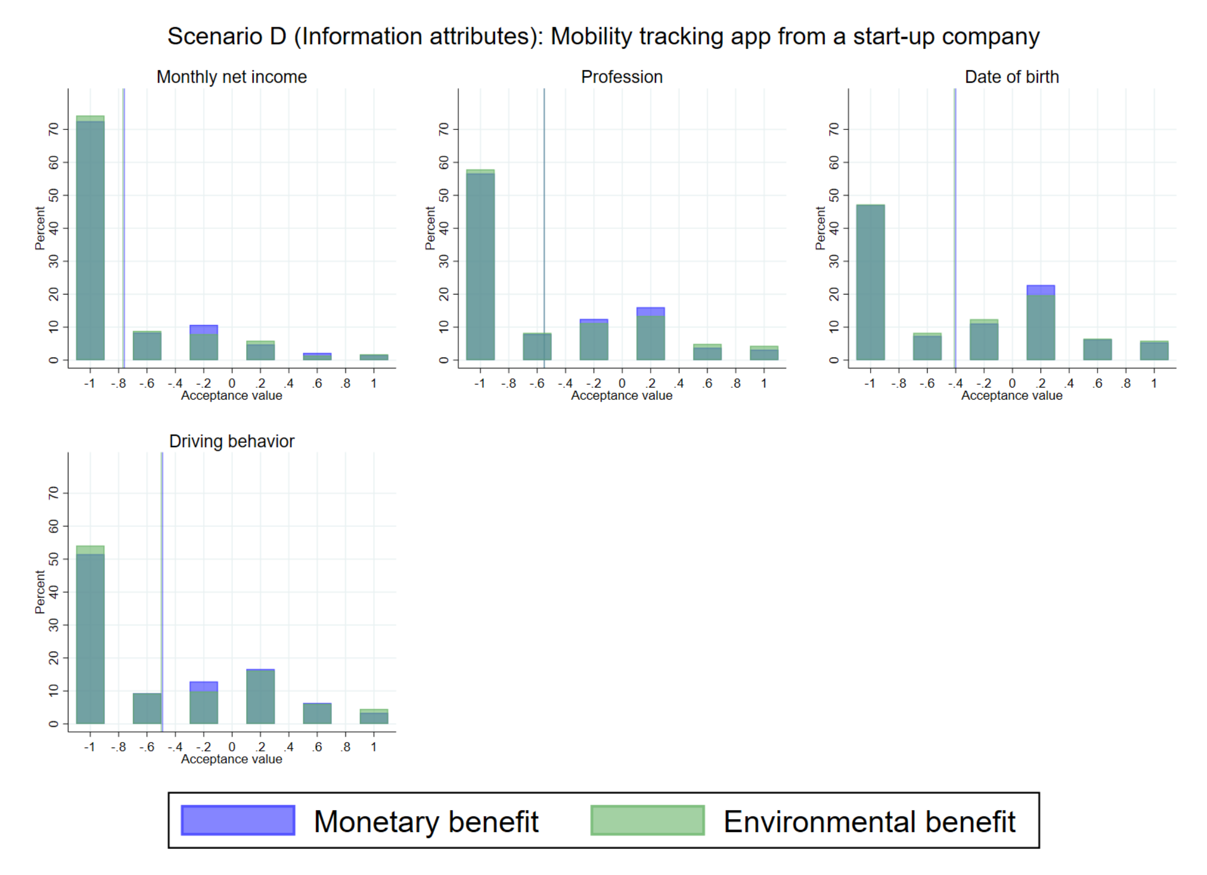

Figure 10: Histograms showing the percentage distribution of acceptance values for optional information attributes in scenario D by treatment. Vertical lines indicate the mean values in T1 (blue) and T2 (green).

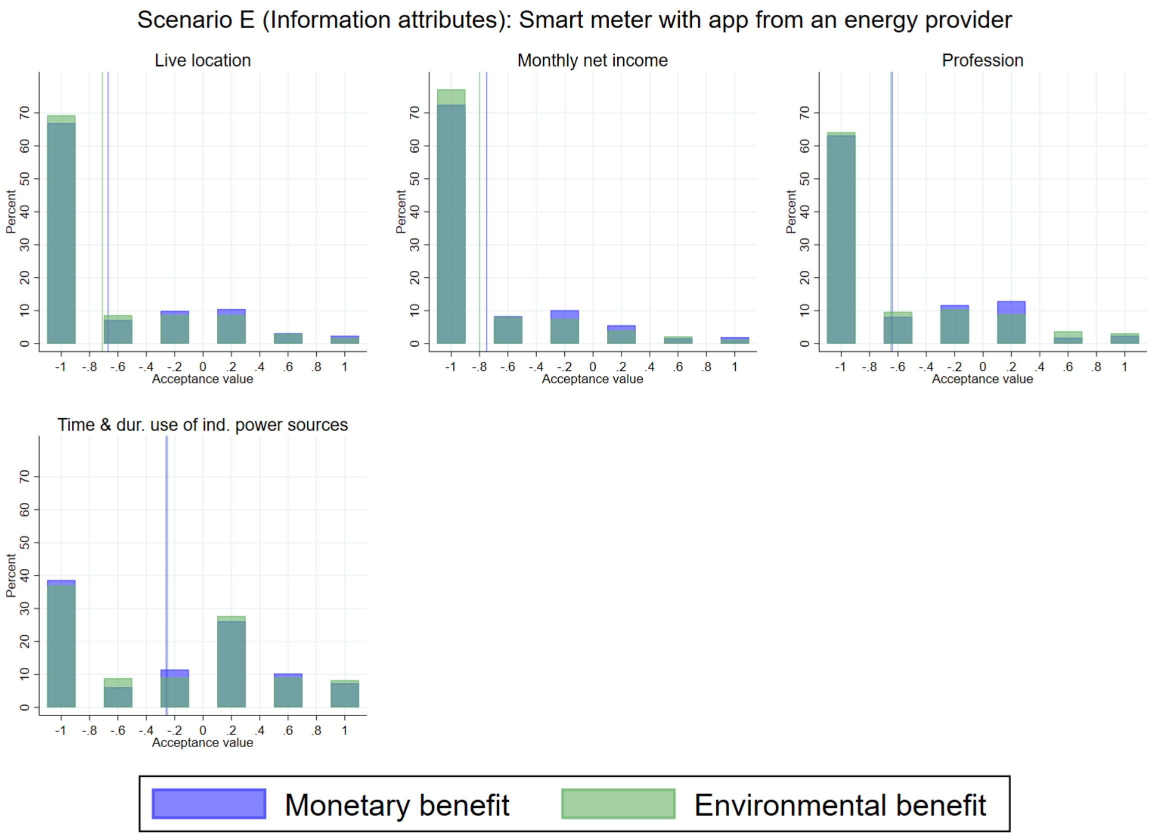

Figure 11: Histograms showing the percentage distribution of acceptance values for optional information attributes in scenario E by treatment. Vertical lines indicate the mean values in T1 (blue) and T2 (green).

Appendix D – Pairwise tests on differences between optional recipients or optional information attributes

Scenario A Loyalty card	Recipient	Household members	Employer	Federal ministries	Market research comp.	German food prod.	American food prod.	Chinese food prod.
Recipient	Acc. value	-0.21	-0.67	-0.39	-0.18	-0.26	-0.64	-0.70
Employer	-0.67	***						
Federal ministries	-0.39	***	***					
Market research comp.	-0.18	not sig.	***	***				
German food producers	-0.26	**	***	***	***			
American food prod.	-0.64	***	not sig.	***	***	***		
Chinese food prod.	-0.70	***	not sig.	***	***	***	***	
Health insurance comp.	-0.48	***	***	***	***	***	***	***

Table 11: Wilcoxon signed rank tests for significant differences between the acceptability scores for optional recipients in scenario A. Average acceptance values for combined treatments are shown in the right column next to each recipient and in the second row. * $p < 0.01$, ** $p < 0.005$, *** $p < 0.001$.

Scenario B Tracking bracelet	Recipient	Household members	Employer	Federal ministries	Market research comp.
Recipient	Acc. value	-0.31	-0.70	-0.46	-0.38
Employer	-0.70	***			
Federal ministries	-0.46	***	***		
Market research comp.	-0.38	***	***	***	
German sports equip. prod.	-0.54	***	***	***	***

Table 12: Wilcoxon signed rank tests for significant differences between the acceptability scores for optional recipients in scenario B. Average acceptance values for combined treatments are shown in the right column next to each recipient and in the second row. * $p < 0.01$, ** $p < 0.005$, *** $p < 0.001$.

Scenario C Nutrition app	Recipient	Household members	Employer	Market research comp.	German food prod.
Recipient	Acc. value	-0.40	-0.75	-0.43	-0.52
Employer	-0.75	***			
Market research comp.	-0.43	not sig.	***		
German food prod.	-0.52	***	***	***	
German Society for Nutrition	-0.40	not sig.	***	**	***

Table 13: Wilcoxon signed rank tests for significant differences between the acceptability scores for optional recipients in scenario C. Average acceptance values for combined treatments are shown in the right column next to each recipient and in the second row. * $p < 0.01$, ** $p < 0.005$, *** $p < 0.001$.

Scenario D Mobility tracking	Recipient	Household members	Employer	Federal ministries	Public transport comp.	Car insurance comp.
Recipient	Acc. value	-0.41	-0.76	-0.52	-0.51	-0.66
Employer	-0.76	***				
Federal ministries	-0.52	***	***			
Public transport comp.	-0.51	***	***	not sig.		
Car insurance comp.	-0.66	***	***	***	***	
City or municip.	-0.58	***	***	***	***	***

Table 14: Wilcoxon signed rank tests for significant differences between the acceptability scores for optional recipients in scenario D. Average acceptance values for combined treatments are shown in the right column next to each recipient and in the second row. * $p < 0.01$, ** $p < 0.005$, *** $p < 0.001$.

Scenario E Smart meter	Recipient	Household members	Employer	Federal ministries	German elect. prod.	Neigh-bors
Recipient	Acc. value	-0.20	-0.79	-0.51	-0.49	-0.78
Employer	-0.79	***				
Federal ministries	-0.51	***	***			
German elect. prod.	-0.49	***	***	not sig.		
Neighbors	-0.78	***	not sig.	***	***	
City or municip.	-0.49	***	***	not sig.	not sig.	***

Table 15: Wilcoxon signed rank tests for significant differences between the acceptability scores for optional recipients in scenario E. Average acceptance values for combined treatments are shown in the right column next to each recipient and in the second row. * $p < 0.01$, ** $p < 0.005$, *** $p < 0.001$.

Scenario A Loyalty card	Information attribute	Food intolerances and allergies	Live location	Nutrition style	Body weight and height
Information attribute	Acc. value	-0.22	-0.60	-0.25	-0.50
Live location	-0.60	***			
Nutrition style	-0.25	not sig.	***		
Body weight and height	-0.50	***	***	***	
Number of steps taken	-0.44	***	***	***	***

Table 16: Wilcoxon signed rank tests for significant differences between the acceptability scores for optional information attributes in scenario A. Average acceptance values for combined treatments are shown in the right column next to each recipient and in the second row. * $p < 0.01$, ** $p < 0.005$, *** $p < 0.001$.

Scenario B Fitness bracelet	Information attribute	Memberships in a sports club or gym	Live location	Nutrition style
Information attribute	Acc. value	-0.44	-0.61	-0.35
Live location	-0.61	***		
Nutrition style	-0.35	***	***	
Body weight and height	-0.37	***	***	not sig.

Table 17: Wilcoxon signed rank tests for significant differences between the acceptability scores for optional information attributes in scenario B. Average acceptance values for combined treatments are shown in the right column next to each recipient and in the second row. * $p < 0.01$, ** $p < 0.005$, *** $p < 0.001$.

Scenario C Nutrition app	Information attribute	Memberships in a sports club or gym	Live location	Food intol. and allergies
Information attribute	Acc. value	-0.52	-0.69	-0.33
Live location	-0.69	***		
Food intol. and allergies	-0.33	***	***	
Monthly net income	-0.74	***	***	***

Table 18: Wilcoxon signed rank tests for significant differences between the acceptability scores for optional information attributes in scenario C. Average acceptance values for combined treatments are shown in the right column next to each recipient and in the second row. * $p < 0.01$, ** $p < 0.005$, *** $p < 0.001$.

Scenario D Mobility tracking	Information attribute	Driving behavior	Profession	Date of birth
Information attribute	Acc. value	-0.50	-0.55	-0.40
Profession	-0.55	**		
Date of birth	-0.40	***	***	
Monthly net income	-0.77	***	***	***

Table 19: Wilcoxon signed rank tests for significant differences between the acceptability scores for optional information attributes in scenario D. Average acceptance values for combined treatments are shown in the right column next to each recipient and in the second row. * $p < 0.01$, ** $p < 0.005$, *** $p < 0.001$.

Scenario E Smart meter	Information attribute	Live location	Profession	Time and dur. of use of ind. power sources
Information attribute	Acc. value	-0.69	-0.65	-0.25
Profession	-0.65	**		
Time and dur. of use of ind. power sources	-0.25	***	***	
Monthly net income	-0.78	***	***	***

Table 20: Wilcoxon signed rank tests for significant differences between the acceptability scores for optional information attributes in scenario E. Average acceptance values for combined treatments are shown in the right column next to each recipient and in the second row. * $p < 0.01$, ** $p < 0.005$, *** $p < 0.001$.

Appendix E – Scales on privacy concerns, risk and GREEN consumption values

Item	Question	Mean (sd)
PC1	I feel uncomfortable when my online behaviors are tracked without permission.	5.63 (1.54)
PC2	I am concerned about misuse of my online behaviors.	5.27 (1.46)
PC3 (R)	It does not bother me to receive too much advertising material through tracking of my online behaviors.	5.20 (1.81)
PC4	I fear that my online behavior information may not be safe while stored.	5.20 (1.44)
PC5 (R)	I do not believe that my online behavioral data is often misused.	4.63 (1.68)
PC6 (R)	I do not think companies share my online behavioral data without permission.	4.76 (1.90)
All six		5.12 (1.03)
Answer: (1) Strongly disagree; (2) Somewhat disagree; (3) Rather disagree; (4) Neither nor; (5) Rather agree; (6) Somewhat agree; (7) Strongly agree		

Table 21: Privacy concern scale (Ham, 2017). Means and standard deviations (in parentheses). (R) denotes reverse items.

Question	Mean (sd)
How do you see yourself: are you generally a person who is fully prepared to take risks or do you try to avoid taking risks? Please tick a box on the scale, where the value 0 means: 'not at all willing to take risks' and the value 10 means: 'very willing to take risks'.	4.33 (2.52)

Table 22: Risk attitude question (Dohmen et al., 2011). Mean and standard deviation (in parentheses).

Item	Question	Mean (sd)
UW1	It is important to me that the products I use do not harm the environment.	5.09 (1.33)
UW2 (R)	I do not consider the potential environmental impact of my actions when making many of my decisions.	4.24 (1.61)
UW3	My purchase habits are affected by my concern for our environment.	4.22 (1.63)
UW4 (R)	I am not concerned about wasting the resources of our planet.	5.31 (1.75)
UW5	I would describe myself as environmentally responsible.	4.92 (1.26)
UW6 (R)	I am not willing to be inconvenienced in order to take actions that are more environmentally friendly.	4.45 (1.67)
All six		4.71 (0.99)
Answer: (1) Strongly disagree; (2) Somewhat disagree; (3) Rather disagree; (4) Neither nor; (5) Rather agree; (6) Somewhat agree; (7) Strongly agree		

Table 23: GREEN consumption scale (Haws et al., 2014). Means and standard deviations (in parentheses). (R) denotes reverse items.