The (In)Effectiveness of Incentives - A Field Experiment on the Adoption of Personal Electronic Health Records

Completed Research Paper

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Abstract

Medication errors are the third-leading cause of death in the US; however, a large number of these cases could be prevented through better medication management. The aging population and the associated high number of individuals taking multiple medications regularly makes medication management even more important. Personal electronic health records (PHRs) can improve medication management significantly and thus increase patient safety. Despite unequivocal benefits for individuals, healthcare professionals, governments, insurers, and employers, the adoption rate of PHRs remains low. Therefore, we seek to identify measures that motivate individuals to adopt PHRs. Drawing on justice theory, we show that incentives in terms of personalization, as well as the signal of fair information practices, increase the adoption rate of PHRs. These effects are mediated by perceived benefits and privacy concerns, respectively. Based on counterintuitive findings on the effects of monetary compensation we start a discussion on the complexity and context-dependency of different incentives.

Keywords: Personal electronic health records (PHRs), financial incentives, personalization, fair information practices, justice theory

Introduction

Worldwide, medical errors are one of the most common and fatal problems of the health sector. They are the third-leading cause of death after heart diseases and cancer, leading to 250,000 deaths in the U.S. every year (Johns Hopkins 2016). Errors include failures in monitoring patients on powerful drugs, poor communication between patients and physicians, or giving patients the wrong medication. Many of these deaths could have been avoided by better medication management. As many elderly people have to take several medications regularly, medication management becomes especially important given the aging population. Personal electronic health records (PHRs), i.e. "electronic health record[s] on an individual that can be […] managed, shared, and controlled by the individual" (Ozdemir et al. 2011, p. 491), have the potential to improve medication management, increase patient safety and support the overall healthcare efficiency significantly (Miller and Tucker 2009; Reti et al. 2009; Vance et al. 2015). PHRs allow individuals to digitally organize and access their personal health information and provide healthcare professionals limited access to relevant information. PHRs can include information on medication adherence or symptoms, as well as information on treatments and diagnosis from doctors, insurance companies or other healthcare professionals. Thereby, PHRs constitute a lifelong, integrated and encompassing overview of the personal health (Markle Foundation 2003). As such, researchers see PHRs as an important building block for the future of health care (Fichman et al. 2011; Raisinghani and Young 2008; Reti et al. 2009).

It comes as a surprise that, despite these huge benefits, the adoption rate of PHRs among individuals remains low (Assadi and Hassanein 2017; Liu et al. 2011; Raisinghani and Young 2008). Previous studies argue that privacy concerns are the main reason for the lack of enthusiasm for PHRs (Agarwal et al. 2013; Goldschmidt 2005; Kaelber et al. 2008; Vance et al. 2015). Privacy concerns relate to the perceived risk of data misuse associated with the disclosure of personal data. Following the notions of the privacy calculus, individuals base their decision to use electronic products and services on a risk-benefit assessment (Culnan and Armstrong 1999; Laufer and Wolfe 1977). In health care, data misuse can have serious consequences due to the sensitive nature of personal health information (Yao et al. 2015). Therefore, the decision to adopt digital health solutions is substantially affected by a complex dilemma between risks and benefits of data sharing (Li et al. 2016).

Integrating privacy calculus and justice theory (Culnan and Bies 2003), we argue that perceived fairness can help to overcome the privacy concerns associated with the disclosure of personal health information. In other words, individuals will disclose personal health information and adopt PHR platforms if they believe that they will be treated fairly within the digital healthcare system. Colquitt et al. (2001, p. 425) suggest that the perception of fairness has two dimensions: Distributive justice, "the fairness of outcome distributions or allocations," and procedural justice, "the fairness of the procedures used to determine outcome distributions or allocations." According to the concept of distributive justice, individuals engage in an exchange process if the ratio of input and output is perceived as fair (Colquitt et al. 2001). The offer of certain incentives in exchange for the disclosure of personal health information could, therefore, increase perceived fairness and thus motivate individuals to adopt PHRs. Align with the theoretical notions of justice theory (Culnan and Bies 2003), we implemented distributive justice in form of monetary compensation and personalized content, i.e. a personal health report that provides individuals with additional information about their health.

According to the concept of procedural justice, transparent, and controllable processes in the exchange relationship increase individuals' perceptions of fairness. As fair information practices implemented by PHR providers signal individuals that their personal health information is being treated in a transparent, respectful, and controllable manner, perceived fairness increases, which in turn is expected to increase the adoption rate of PHRs (Colquitt et al. 2001). Taking all aspects into consideration, we ask: Can distributive justice in form of financial incentives and personalization incentives, and procedural justice in form of the signal of fair information practices, promote the adoption of PHRs?

To answer this question, we conducted a randomized controlled field experiment with a sample of 216 participants. In cooperation with eHealth ventures, a provider of the PHR application POLAVIS VIVA, we examined the effects of financial incentives, personalization incentives, and fair information practices on individuals' privacy concerns, perceived benefits, data provision behavior, and opt-in behavior on POLAVIS VIVA. Our results demonstrate that personalization incentives increase the PHR adoption rate significantly and that this effect is mediated by the benefits perceived by the individual. Moreover, we show that fair information practices increase the PHR adoption rate significantly. Our analyses further suggest that privacy concerns mediate this relationship. However, it comes as a surprise that financial incentives, in contrast to personalization incentives and fair information practices, do not increase the adoption rate. We suggest that even though the three organizational measures address fairness perceptions, they are perceived and attributed differently by individuals in the healthcare context. While personalization incentives and fair information practices directly or indirectly relate to the PHR platform, monetary compensation constitutes a value that is independent of the ultimate purpose of PHRs, i.e. improving individuals' healthcare management. Thus, we emphasize that the components of justice are more complex and context dependent than previously assumed.

This article contributes to the literature on health information technology adoption in three ways. First, we contribute to the theoretical understanding of PHR adoption decisions by applying an overarching justice theory framework. Previous studies are mainly based on privacy calculus and technology acceptance models (Li et al. 2016); however, justice theory provides promising yet unanalyzed solutions to advance the adoption of PHRs. Second, we examine the role of incentives for PHR adoption (Anderson and Agarwal 2011). As PHRs drive the overall digitization of health care (Romanow et al. 2012), the identification and analysis of measures that support PHR adoption decisions are crucial. No previous study has analyzed the impact of different incentives on health information technology adoption among individuals. Third, we use a randomized controlled field experiment to test our hypotheses. This allows us to measure actual behavior instead of attitude or behavioral intention. Evidence on actual PHR adoption is still scarce, but particularly important given the often discussed attitude-behavior gap (Acquisti et al. 2015).

Conceptual Background

Personal health data is attributed by individuals as one of the most sensitive information (Angst and Agarwal 2009; Bansal et al. 2010). Therefore, data privacy concerns constitute a major barrier to the disclosure of personal health information, i.e. information that can be assigned to an individual (Culnan and Bies 2003). Subsequently, the dissemination of data-driven health technologies is inhibited. Information privacy is defined as the ability of individuals to control the conditions under which their personal information is collected and used (Culnan and Bies 2003). Information privacy research argues that individuals base their decision to use electronic products and services on a risk-benefit assessment known as the privacy calculus (Culnan and Armstrong 1999; Laufer and Wolfe 1977). The privacy calculus proposes that individuals will disclose personal information online if they perceive that the benefits of disclosure exceed the risks (Culnan and Armstrong 1999; Dinev and Hart 2006; Smith et al. 2011). Thus, individuals will accept the risks in exchange for sufficient benefits provided by the counterpart (Dinev et al. 2013). The privacy calculus has been frequently applied in information privacy research. Even though health data are considered to be the most sensitive type of data (e.g. Bansal et al. 2010), we draw our theorizing also from leading information systems studies analyzing financial or location-based data. In this regard, the studies of Angst and Agarwal (2011), Dinev and Hart (2006), Kehr et al. (2015), Xu et al. (2009), or Xu et al. (2011) are particularly noteworthy as they provide valuable insights into online privacy behavior. All of the named studies apply the privacy calculus as their main theoretical framework.

To further examine the privacy calculus and enhance the understanding of individuals' decision making regarding the disclosure of personal information, Culnan and Bies (2003) combine the privacy calculus with a justice theory perspective. They propose that individuals conduct the risk-benefit assessment predicted by the privacy calculus, but that the resulting behavioral decisions depend on the perceived fairness within the exchange relationship. In other words, "the outcomes of risk-benefit analysis of personal information disclosure, at the individual level, could be differentiated according to the extent to which justice provisions are manifested in privacy interventions" (Xu et al. 2009, p. 139).

According to justice theory, perceived fairness is represented by different dimensions of justice. Among scholars, there is controversy about the number of dimensions; however, following a meta-analysis of 183 justice theory studies of Colquitt et al. (2001), the two subordinate components influencing individuals' decisions about disclosing information are distributive justice and procedural justice.

Distributive justice refers to the perceived fairness of the output individuals receive in exchange for the disclosure of their personal information. According to distributive justice, individuals base their behavioral decisions on an assessment of provided input and received output (Colquitt et al. 2001). If they perceive a fair input-output ratio, individuals will disclose their information. Following Culnan and Bies (2003), we suggest that value in terms of financial compensation and personalization can increase individuals' perceptions that distributive justice is present. Both financial and personalization incentives constitute additional benefits in exchange for personal health information and should, in turn, increase the likelihood of PHR adoption. However, regarding the mechanisms of incentives the PHR context differs from e-commerce or other contexts that involve a monetary exchange. Whereas financial incentives in terms of monetary compensation do not directly support the ultimate objective of PHRs, personalization incentives directly increase the utility of PHRs through advanced content tailored to the individuals.

Procedural justice refers to the perceived fairness of information collection and use (Xu et al. 2009). If individuals perceive that they have control over the process of collection and use of their personal health information, the exchange relationship will be perceived as fair and privacy concerns will be mitigated. As a result, individuals will be more likely to disclose their personal information. Following Culnan and Bies (2003), procedural justice can be implemented through fair information practices. Fair information practices signal individuals that their information privacy is being treated in a respectful manner, and thus that the organization can be trusted (Culnan and Bies 2003; Xu et al. 2009). As a result, privacy concerns are reduced. According to Schwaig et al. (2006), fair information practices include five core principles: Notice of data collection and use, consent and choice about data collection and data sharing with third parties, access to and modification of information, security to prevent unauthorized access, and enforcement to ensure the compliance of the firm with these data privacy principles. As fair information practices signal to individuals that their personal information is treated in a transparent and controllable manner, we argue that procedural justice in terms of fair information practices increases the perceived fairness and in turn the likelihood of PHR adoption.

Hypotheses

Distributive Justice

The fear of data misuse and unauthorized dissemination of data constitute a key barrier for individuals in sharing their personal information (Xu et al. 2012). Misuse of personal health data can have serious consequences, leading to privacy concerns that are preventing individuals from the adoption of new technologies. However, following Culnan and Bies (2003), organizations can mitigate the privacy concerns if they improve individuals' distributive justice perceptions. The concept of distributive justice reflects the fair allocation of output that individuals receive in return for the input provided. Culnan and Bies (2003) theorize that individuals assess the output they expect to receive in exchange for providing their personal information to organizations. To motivate individuals to disclose personal information, the value of the output should compensate for the value of the personal information. Therefore, we expect that individuals will adopt PHRs if they perceive a fair output in exchange for the input of personal health information.

Financial Incentives

The input-output assessment associated with the usage of PHR platforms is complex and multifaceted as risks and benefits can hardly be quantified. However, the subjective benefits can be increased through the offer of rewards in exchange for the disclosure of personal data (Hui et al. 2007; Premazzi et al. 2010). In this regard even small rewards can outweigh the privacy concerns and motivate individuals to disclose personal information (Acquisti and Grossklags 2005). Laufer and Wolfe (1977) argue that individuals will disclose personal information in exchange for financial benefits. Financial benefits represent an additional value that improves the subjective input-output assessment and improves perceptions of distributive justice (Xu et al. 2009).

However, two underlying mechanisms of financial incentives have to be taken into account that partly contradict the notions of justice theory. First, Gneezy et al. (2011) identified counter effects of financial incentives. Apart from the positive effect, financial incentives can also trigger a negative effect on the incentivized behavior by increasing the awareness that the counterpart collects and uses personal information (Gneezy et al. 2011). This effect has been found to be particularly salient in contexts of high risks and uncertainties (Hoffman et al. 1999), thus the context of sensitive health information can be critical (Bansal et al. 2010). Second, whereas the value of financial incentives is directly context related in e-commerce settings or other contexts that involve a monetary exchange, monetary compensation is not related to PHRs and thus only provides a context unrelated value in our study.

Yet, prior research shows predominantly positive effects of financial incentives on data disclosure decisions and attitudes. For example, findings of Hui et al. (2007) show in the context of computing products that monetary compensation in form of a check has a positive influence on data disclosure decisions. Cichy et al. (2014) support this finding for the context of personal driving data. Premazzi et al. (2010) demonstrate in an e-commerce setting that even though participants did not claim that they would be more prone to provide information in return for monetary incentives in form of an online retail coupon, they actually were. Furthermore, Xu et al. (2009) prove in the context of location-based services that financial incentives in form of a discount on the monthly phone bill can increase perceived benefits.

Drawing on the empirical findings of prior literature and on the theoretical notions of justice theory, we propose that PHR platform providers can improve individuals' fairness perceptions of the outcomes through the provision of financial incentives. Consequently, we argue:

Hypothesis 1. Organizations can increase the rate of PHR adoption if they provide financial incentives as a means to improve the individuals' perception of distributive justice.

Personalization Incentives

In general, personalization refers to content that is tailored to individuals based on knowledge about those individuals (Adomavicius and Tuzhilin 2005). There is a clear trend for firms using consumer information for personalization purposes (Awad and Krishnan 2006). In the healthcare domain, personalization offers unparalleled opportunities for value creation. The improvements in access to health data and in communication with healthcare providers through PHRs enable health care to be tailored to individual needs (Fichman et al. 2011). Furthermore, personalization in health care increases the efficiency of diagnosis processes and reduces medication errors (Reti et al. 2009; Vance et al. 2015).

The personalization-privacy paradox (Awad and Krishnan 2006) plays a central role in the impact of personalization on behavioral decisions. Personalizing content and services to the individual is strongly related to data privacy because it involves large amounts of personal information (Xu et al. 2011). As personalization creates value only through the inclusion of personal information, personalization increases both perceived benefits and risks, leading to a dilemma in individuals' decision-making process. Thus, individuals who are more concerned about data privacy are less likely to participate in personalization (Awad and Krishnan 2006).

However, following the concept of distributive justice, value in terms of personalization has a positive effect on data disclosure decisions. According to Culnan and Bies (2003), along with the monetary exchange, distributive justice also consists of a non-monetary exchange, which they term "second exchange," and in which individuals provide their personal information in return for personalized content or higher quality services. Following the concept of distributive justice, individuals provide their personal information if the input-output ratio is perceived as fair. As personalization constitutes an additional benefit, we argue that the provision of personalization incentives in exchange for personal health information can positively influence the individuals' input-output assessment.

Empirical evidence on the impact of personalization is inconsistent. Ward et al. (2005) could not find a significant effect of personalization incentives on the willingness to provide personal information in an online shopping context. By contrast, Awad and Krishnan (2006) and Chellappa and Sin (2005) show in an online service provider setting that personalized services increase perceived utility and in turn the likelihood of usage. Moreover, Xu et al. (2011) show that personalization incentives can significantly increase both perceived risks and benefits in the context of location-aware marketing. These results have all been found in different contexts. Therefore, we argue that the perceived benefits of personalization are strongly context dependent. Awad and Krishnan (2006) support this line of argumentation. They suggest that the effect of personalization on the behavior of individuals depends on the value that personalization creates. Whereas e-commerce settings involve an exchange of money, PHRs are about improving the healthcare situation of individuals. This inherent goal can be directly supported through the offer of personalized content and services. Thus, individuals should attribute a particularly high importance to personalization in the context of PHR adoption.

Drawing on justice theory, we argue that the offer of personalization incentives should increase individuals' perceptions of positive outcomes of the privacy calculus through an improvement in those individuals' distributive justice perceptions (Culnan and Bies 2003). Consequently, we propose the following hypothesis:

Hypothesis 2. Organizations can increase the rate of PHR adoption if they provide personalization incentives as a means to improve the individuals' perception of distributive justice.

Procedural Justice

According to justice theory, perceptions of fairness in the context of information privacy arise not only through an exchange of benefits in return for information disclosure but also through fair processes in the collection and use of information (Culnan and Bies 2003; Xu et al. 2009). In other words, the way organizations treat the information will be reflected in the behavioral decisions of individuals (Culnan and Bies 2003). The concept of procedural justice states that if individuals perceive a fair treatment within the information exchange process, their willingness to disclose personal information increases (Culnan and Bies 2003). Fair information practices provide individuals with control and voice over the disclosure and subsequent use of their data (Culnan and Bies 2003). Because fair information practices ensure that organizations comply with privacy principles, they align the interests of individuals and organizations and serve as a social contract. Fair information practices provide a solution to increase perceived fairness and minimize privacy concerns. They signal to individuals that their information privacy is treated in a respectful manner and thus that the organization can be trusted (Culnan and Bies 2003; Xu et al. 2009). This form of trust is especially important in online contexts as the exchange relationship is characterized by uncertainty and social distance. Using PHR platforms, individuals rely on strangers to manage their highly sensitive personal health information. Therefore, trust-enabling mechanisms, as features of fair information practices, reduce privacy concerns and can subsequently increase the adoption rate of PHRs (Culnan and Bies 2003; Xu et al. 2009).

Evidence on the impact of fair information practices is contradictory (Tsai et al. 2011). Results of Belanger et al. (2002) do not show a positive impact of privacy seals in an e-commerce context. Hui et al. (2007) support this finding using a computing products setting. By contrast, empirical results of Culnan and Armstrong (1999) provide evidence that emphasizing fair information practices can alleviate consumers' data privacy concerns to disclose data for marketing purposes.

Following the theoretical notions of procedural justice, we propose the following hypothesis:

Hypothesis 3. Organizations can increase the rate of PHR adoption if they signal fair information practices as a means to improve the individuals' perception of procedural justice.

Mediation Effects

We combine privacy calculus and justice theory to explain the underlying mechanisms of the effects of financial incentives, personalization incentives, and fair information practices on PHR adoption. According to distributive justice individuals base their behavioral decisions on a risk benefit assessment. To induce individuals to adopt PHR platforms, the benefits should compensate for the value of the personal data. The provision of financial incentives and personalization incentives should increase the perceived benefits and in turn increase PHR adoption rates. Furthermore, following the concept of procedural justice, individuals value fairness of the collection process and use of personal data. As fair information practices signal to individuals that their data is treated in a fair and ethically correct manner, fair information practices should decrease privacy concerns and lead to an increase in PHR adoption rates.

Building on these theoretical underpinnings, we pose the following mediation hypotheses:

H4: The effects of financial incentives (a) and personalization incentives (b) on the PHR adoption rate are mediated by perceived benefits. The effects of fair information practices on the PHR adoption rate are mediated by privacy concerns (c).

Figure 1 illustrates our conceptual model.

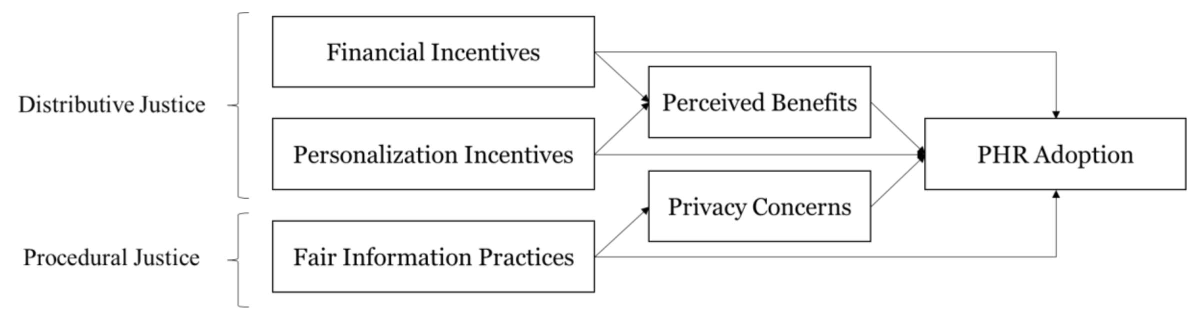

Figure 1. Research Model

Method

Experimental Design

In cooperation with eHealth ventures, a provider of mobile health solutions in Germany, we conducted a randomized controlled field experiment. The experimental setting allows us to observe causal effects about actual PHR adoption rates. We designed the experiment as follows. First, participants received an e-mail invitation to register for POLAVIS VIVA (https://www.polavis-viva.de/en/), a PHR application hosted by eHealth ventures. The invitation e-mails contained a short description of the PHR functions to ensure that all participants had a common understanding. These functions include, among others, communication with health professionals, long-term data storage, medication monitoring, or appointment management.

Furthermore, we included the treatment of each scenario and the registration link in the e-mails. All e-mails had the same subject line and pre-header (the text below subject line in the inbox). Hence, we introduced the treatments only after participants opened the e-mails. Analogous to the three independent variables, our experiment contained three treatments: financial incentives, personalization incentives, and fair information practices. As a control group, we also added a base scenario that simply invited the recipient to use POLAVIS VIVA without offering any incentives. In the first treatment, participants were told that they would receive a five euros Amazon voucher as a welcome gift via e-mail after registration. We chose the amount of five euros based on similar experimental settings of related literature (e.g. Hui et al. 2007). In the second treatment, eHealth ventures implemented personalization incentives in the form of a personal health report given to participants based on their data provided on POLAVIS VIVA. The report provided the user with personalized health-related information and statistics on their medical history. Individuals were not required to provide additional information and could download the report on the app in PDF format. The personal health report developed by eHealth ventures complied with the definition of personalization introduced above (Adomavicius and Tuzhilin 2005). In the third treatment, participants were told that the data privacy practices of POLAVIS VIVA comply with the highest security standards in Germany and are certified by the IPS data privacy seal, a nationwide data protection standard for online services. We chose a data privacy seal to signal fair information practices in contrast to a privacy statement since only measures that go beyond legal standards will make a difference for the behavioral decisions of individuals (Awad and Krishnan 2006). As privacy statements are legally binding in most countries, only privacy seals or other data privacy certificates that go beyond legal standards constitute appropriate measures for organizations to stand out in regard to their information practices (Awad and Krishnan 2006). None of the three treatments required any additional effort that might influence the cost-benefit assessment of individuals. In the invitation e-mails, we highlighted the respective treatment by both text and pictures to draw the attention of participants to the treatment. In addition to the general introduction of POLAVIS VIVAs functions and the written description of the treatments, the first treatment included a picture of an amazon voucher, the second treatment a picture of the personal health report, and the third treatment showed the IPS data privacy seal.

Corresponding to the four scenarios, eHealth ventures created one landing page for each of the four scenarios. This method is necessary for three reasons. First, it enables matching of the registrations to the respective treatment. Second, it avoids unintentional overlaps between the scenarios. These overlaps could arise when participants of one scenario have access to the landing pages of other scenarios. Third, it guarantees that we included only those participants that received the experimental e-mail into the sample. In other words, we did not consider individuals that registered for POLAVIS VIVA through the original landing-page. One week after sending the e-mail invitations, we sent a follow-up questionnaire to those participants who had opened the invitation e-mail. Through e-mail addresses, we matched back registration behavior to the information participants provided in the follow-up questionnaire. Whether participants answered the follow-up questionnaire or not was independent of the treatments.

Operationalization of Variables

We included the three treatments of financial incentives (Financial), personalization incentives (Personalization), and fair information practices (FIP) in the final model as dummy variables. The dependent variable Registration describes through a dummy variable the opt-in behavior for POLAVIS VIVA. Moreover, we observed the number of health data provided on POLAVIS VIVA after opt-in. However, since we did not find any significant differences in the number of health data provided by individuals after they registered for POLAVIS VIVA, we use, like Angst and Agarwal (2009), PHR adoption as a synonym for opt-in behavior. The follow-up questionnaire included gender, age, and education to assess the demographic characteristics of the participants. Since individuals often indicate an attitude different from their actual behavior (Acquisti et al. 2015), we asked participants to state their attitude towards a PHR platform like the one of eHealth ventures (Attitude). We applied the three-item attitude scale of Angst and Agarwal (2009). Furthermore, we included scales for Privacy Concerns, adapted from Pavlou et al. (2007), and Perceived Benefits, adapted from Xu et al. (2011) into the follow-up questionnaire. The scale for privacy concerns contained three items, asking individuals if they are afraid of privacy violations when using PHR platforms like POLAVIS VIVA, e.g., "I am concerned about my privacy when using PHR platforms like POLAVIS VIVA." The perceived benefits scale asked individuals how beneficial they expect PHR platforms like POLAVIS VIVA to be in regard to healthcare management, e.g., "Overall, I feel that using PHR platforms like POLAVIS VIVA is beneficial." The three scales have each been assessed through three items on seven-point Likert scales. Throughout the whole questionnaire, we kept the scales as close as possible to the original. As the participants of our study were not retrieved from survey pools and are thus not necessarily familiar with answering questionnaires, we applied comparably short scales to reduce dropout rates. Before conducting the experiment, we refined the design of the treatment conditions and the follow-up questionnaire through pretesting.

Manipulation Checks

To verify the effectiveness of our treatments, we included manipulation checks into the follow-up questionnaire. Participants had to select the treatment they received among all four treatments to check whether they had paid attention to their treatment. In addition, we included specific questions to check whether the scenarios had the desired effect on the participants' beliefs. First, to verify the manipulation of financial incentives, we asked whether participants believe that POLAVIS VIVA provides financial incentives for participation. Second, to verify the manipulation of personalization incentives, we asked whether participants believe that POLAVIS VIVA provides personalized content and services based on the individuals' health data. Third, to verify the manipulation of fair information practices, we asked whether participants believe that POLAVIS VIVA takes measures to protect their personal data.

Data Collection and Cleaning

In total, 250,000 participants received the e-mail invitation to register for POLAVIS VIVA. A marketing agency, which had collected the e-mail addresses via a double opt-in procedure, sent out both e-mails. We decided to use this method of participant recruitment instead of standard experiment pools to create real conditions. Participants of standard experiment pools could anticipate our experimental setting, which in turn could bias the results. Furthermore, the marketing agency guaranteed that the sample was representative of the German adult population. We divided the total sample randomly into four groups with 62,500 participants each, corresponding to the four scenarios. Irrespective of whether the participants had registered for POLAVIS VIVA, all those who opened the first e-mail received the invitation to participate in the follow-up questionnaire.

Of the initial mailing list, 6.6% of participants opened the first e-mail and thus received the request to participate in our follow-up questionnaire. Of the participants that received the follow-up e-mail, 3,358 participants opened the follow-up e-mail, and 276 participated in the follow-up questionnaire. We excluded two participants who registered for POLAVIS VIVA, as they did not participate in the follow-up questionnaire. This was necessary for two reasons. First, to create the dataset, we had to match the e-mail addresses collected during the registration process with the e-mail addresses from the follow-up questionnaire. Second, to conduct the experiment in an ethically correct manner, we asked participants in the follow-up questionnaire explicitly for their consent to the use of their data for the purpose of our study. Furthermore, we did not include participants who registered for POLAVIS VIVA after the follow-up questionnaire was sent out. Since the follow-up questionnaire made participants aware of the experimental setting, this step was necessary to maintain the explanatory power of a field experiment. Our final data set consists of 216 participants of which 48 registered for POLAVIS VIVA. Of the 216 participants that answered the follow-up survey, 53 received financial incentives, 57 personalization incentives, 55 fair information practices, and 51 received none of the three treatments. Of those that registered, 10 received financial incentives, 16 personalization incentives, 14 fair information practices, and 8 did not receive any of the three treatment conditions.

Analysis

The Shapiro-Wilk test of normality revealed that the error terms are not normally distributed. As probit regression assumes a normal distribution of the error terms, we applied a logit regression function. The individuals' decisions to use PHR platforms are largely determined by their attitudes towards PHR platforms. Since we set out to analyze how incentives can change PHR adoption rates given this pre-existing attitude, we included attitude into the regression as a control variable. As the follow-up survey was conducted after participants were exposed to the treatments, we included the regression residual of attitude on financial incentives, personalization incentives, and fair information practices (rAttitude). This residual reflects the pre-existing attitude towards the PHR platform independent of the treatments. To further check the robustness of our model, we have tested the effects when including demographic variables such as age, gender, and education as additional control variables. The results remain virtually the same. Furthermore, to validate our line of argumentation regarding distributive and procedural justice, we conduct binary-mediation analyses in which the effects of financial incentives, personalization incentives, and fair information practices on the adoption rate are mediated by perceived benefits and privacy concerns, respectively. As the mediator is continuous whereas the dependent variable is binary, mediation requires a combination of OLS with either probit or logit models (Kenny, 2008). Therefore, we compute indirect effects with standardized coefficients. To receive standard errors and confidence intervals, we bootstrapped binary-mediation with 5,000 replications.

Results

Descriptive Statistics

The average age is 44.4 years. The gender distribution of our sample is 56% female and 42% male with 2% of participants not revealing their gender. Compared to the average of the German population, the education of our participants is relatively high, with 37.8% holding a high school degree or higher education. The education characteristics are comparable between the participants that registered (group 1) and those that did not register (group 2). In terms of gender, the distribution between the two groups differs slightly. Group 1 includes 2.55% more women than group 2. The age structure varies slightly between the groups. The age average among group 1 is 48.45 years, while the age average among group 2 is 43.22 years. The scales for attitude, privacy concerns and perceived benefits performed well with Cronbach's alpha values over 0.80.

Results from Regression Analysis

Table 1 depicts the results of the logit regression and average marginal effects for interpreting the effect sizes. Our final model reports a McFadden Pseudo R^2 value of 0.24, indicating good model fit with the data. In addition, the likelihood ratio Chi-square test (Chi-square = 55.40; p = 0.00) as well as the Hosmer-Lemeshow test (Chi-square = 7.25; p = 0.51) confirm that our model fits the data well. In Hypothesis 1, we suggested that financial incentives increase PHR adoption rates. The logit regression does not show a significant effect of financial incentives on PHR adoption (coefficient = 0.61; p = 0.33). Therefore, we do not support Hypothesis 1. However, our results support Hypothesis 2, predicting that personalization incentives increase PHR adoption rates. The calculation of the marginal effects reveals that the offer of personalization incentives significantly increases PHR adoption rates, on average by 19.70 % at the one percent level. Moreover, the calculation of the marginal effects confirms Hypothesis 3 by revealing that fair information practices significantly increase PHR adoption rates on average by 17.39 % at the five percent level. We further calculated the percentage of cases correctly classified by our model. Overall, the classification results show a correct specification for 78.24% of the participants.

Table 1. Logit Regression Results and Average Marginal Effects

Registration	Coefficients of logit regression	Average marginal effects dy/dx in %
Financial	.61 (.63)	7.80 (.08)
Personalization	**1.51* (.61)**	**19.70** (.08)**
FIP	**1.34* (.61)**	**17.39* (.08)**
rAttitude	**1.15*** (.20)**	**15.00*** (.02)**
Constant	**-2.80*** (.56)**	
McFadden Pseudo R^2	.24	
Subjects	216	216

Note. Standard errors are reported in parentheses. Results controlling for age, sex, and education are virtually the same and are therefore not included in the table. The abbreviation FIP stands for fair information practices. Significant effects are written in bold. * p < .05, two-tailed test, ** p < .01, two-tailed test, *** p < .001, two-tailed test

Mediation Analyses

As in the regression analysis, we could not find any significant mediation effects for financial incentives. However, our results reveal at the five percent level significantly positive indirect and total effects for personalization incentives indicating full mediation of personalization on PHR adoption through perceived benefits. Furthermore, for the effect of fair information practices on PHR adoption through privacy concerns, the results reveal significant positive indirect and total effects, again indicating a full mediation at five percent level. Thus, our results support H4b and H4c. Table 2 shows the standardized coefficients of indirect, direct and total effects as well as confidence intervals of the described mediation analyses.

Table 2. Binary-Mediation Analyses

	Financial Incentives		Personalization Incentives		Fair Information Practices	
	Obs. Coeff.	*95% CI*	Obs. Coeff.	*95% CI*	Obs. Coeff.	*95% CI*
Indirect Effect	-.01(.02)	[-.06|.04]	**.11 (.06)**	**[.01|.23]**	**.07 (.03)**	**[.01|.14]**
Direct Effect	.16(.14)	[-.13|.45]	.24 (.14)	[-01|.52]	.19 (.14)	[-.08|.48]
Total Effect	.15(.15)	[-.14|.45]	**.35 (.13)**	**[.11|.59]**	**.26 (.14)**	**[.00|.53]**

Note. Standardized bootstrap results with 5000 replications are reported. Bootstrap standard errors are reported in parentheses. The abbreviation CI stands for confidence interval. Significant effects are written in bold.

To deepen our understanding on the influences of personalization incentives and fair information practices on PHR adoption we examine whether perceived benefits and privacy concerns are significantly different among the treatment conditions. The analysis of variance (ANOVA) results show that on average perceived benefits are lowest for financial incentives, followed by fair information practices, and personalization incentives with the highest value of perceived benefits. The average value of privacy concerns is lowest for fair information practices, followed by personalization incentives, and financial incentives with the highest value of privacy concerns. All differences are statistically significant at one percent level.

Discussion

The findings of our study show that personalization incentives - as implemented in our study - increase PHR adoption. According to distributive justice, individuals conduct an input-output assessment before disclosing their personal information online. If the perceived output compensates for the data input, individuals will perceive the exchange as fair and thus disclose their information online. Personalized content in exchange for personal information constitutes an additional benefit that increases the perception of distributive justice (Culnan and Bies 2003). Following justice theory, the offer of personalization incentives should thus increase distributive justice perceptions and increase the likelihood of PHR adoption. Therefore, our result is in line with the arguments of justice theory. However, in the derivation of Hypothesis 2 we demonstrated that the findings of previous literature are inconsistent. The personalization-privacy paradox provides an explanation for the contradictory results. Personalization increases both perceived benefits and risks since the value of personalization arises only through the inclusion of personal information. Thus concerns regarding the disclosure of personal data in exchange for personalization could outweigh the benefits (Awad and Krishnan 2006; Xu et al. 2011). As stated above, personalization offers particular value in the healthcare context. The benefits that personalization incentives provide for individuals are especially evident when it comes to improvements in diagnosis and treatments as well as increased patient safety (Fichman et al. 2011; Reti et al. 2009; Vance et al. 2015). The personalization incentives implemented in our experiment contribute to the inherent benefits of PHRs and thereby, support the ultimate objective of PHRs. Therefore, we argue that the high value that personalization offers in health care compared to other areas is a possible explanation for the relatively strong positive effect of personalization incentives in our experiment.

Our results also reveal that fair information practices - as implemented in our study - significantly increase the likelihood that individuals will adopt PHR platforms. According to justice theory, fair information practices serve as a signal that the organization treats personal information in a respectful and transparent manner. Subsequently, privacy concerns decrease and the willingness to disclose personal information increases (Culnan and Bies 2003). Therefore, our finding of a positive effect of fair information practices on the adoption rate of PHRs is in line with the theoretical notions of justice theory. Nevertheless, as shown in the derivation of Hypothesis 3 studies conducted in different cultural and contextual backgrounds show contradictory results. We see two reasons for the comparably strong effect of fair information practices in our study. First, Germany is particularly conservative with regard to data protection (Hofstede 1980). As we conducted the experiment in Germany, participants in our study could have been culturally influenced. Second, in the PHR context data privacy is of particular importance due to the high sensitivity of personal health information. Thus, participants of our study could have assigned a higher value to data privacy than in other commercial settings (e.g. Hui et al. 2007).

Beyond that, we did not find a significant effect of financial incentives on PHR adoption. As the concept of distributive justice predicts that financial incentives constitute an additional benefit that increases perceptions of justice and subsequently makes the incentivized behavior more likely (Culnan and Bies 2003), our finding does not support the notions of justice theory. We see three interrelated explanations for the insignificant effect. First, prior research identified two counter-effects of financial incentives (Gneezy et al. 2011). On the one hand, financial incentives have a direct effect that has a positive impact on the incentivized behavior. On the other hand, financial incentives can also trigger an indirect effect that works in the opposite direction and thus makes the incentivized behavior less likely, as they can provoke the awareness that the counterpart collects and uses personal information. Hence, financial incentives can imply high risks of data disclosure. Moreover, the offer of financial incentives can evoke the negative feeling of selling personal data and subsequently increase privacy concerns (Gneezy et al. 2011). Following this line of argumentation, the incentivized behavior becomes less likely despite the monetary value of financial incentives. According to Hoffman et al. (1999), the positive effect of financial incentives is invalidated in contexts of high risks and uncertainties. Previous literature provides clear evidence that health data is comparatively sensitive and thus associated with risk and uncertainty (Bansal et al. 2010; Kam and Chismar 2006; Rohm and Milne 2004). Bansal et al. (2010) show that an increase in perceived data sensitivity significantly increases privacy concerns, which in turn lowers the intention to disclose sensitive health information. Second, we argue that the effect of incentives depends on the context relatedness, i.e. whether financial incentives contribute to the ultimate purpose of the incentivized behavior or not (Promberger et al. 2012). In our study, financial incentives only provide a monetary value that is independent of the inherent benefit of PHRs. By contrast, in contexts that naturally involve a monetary exchange, financial incentives provide a direct contribution. Therefore, incentives like personalized content or services that improve the healthcare situation of individuals directly might be more efficient in supporting PHR adoption. The study of Promberger et al. (2012) supports this line of argumentation. Investigating the effects of different financial incentives to change health related behavior they find that vouchers for healthy grocery were more efficient than vouchers for luxury items. Thirdly, building on this, we argue that the impact of financial incentives depends on the way of implementation (Promberger et al. 2012; Volpp et al. 2008). We implemented financial incentives as a monetary compensation that is not related to health care. However, there are ways to relate financial incentives to the purpose of PHRs. For example, insurance companies or employers offering PHRs could provide users with a reduction of the insurance premium or other healthcare related savings. By linking the financial incentive to the purpose of PHRs, we expect stronger effects on the incentivized behavior (Promberger et al. 2012).

Theoretical Implications

Our study contributes to health information technology and privacy research in three ways. First, we close an important gap in health information technology adoption literature by examining the role of incentives (Anderson and Agarwal 2011). Previous research in the health information technology field largely focused on behavior-related beliefs of the individuals and risk-related factors to explain adoption decisions (Li et al. 2016). In this regard, the effects of perceived usefulness and perceived ease of use (Guo et al. 2013; Hung et al. 2014; Lishan et al. 2009; Maass and Varshney 2012; Miltgen et al. 2013; Moores 2012; Wu et al. 2011), privacy concerns (Anderson and Agarwal 2011; Angst and Agarwal 2009; Li 2014b; Miltgen et al. 2013), technology anxiety (Guo et al. 2013; Lim et al. 2011), and trust (Anderson and Agarwal 2011; Miltgen et al. 2013) have been often examined. Although empirical evidence on the effects of these factors is important to understand PHR adoption, evidence on the impact of incentives can help organizations to drive health information technology adoption. As this evidence was still missing (Anderson and Agarwal 2011), we have extended previous research by analyzing the impact of financial incentives and personalization incentives on PHR adoption decisions. The investigation of incentives is of further importance since the personalization-privacy paradox (Awad and Krishnan 2006), the context dependency, and the aforementioned counter-effects of financial incentives (Gneezy et al. 2011; Hoffman et al. 1999) raise ambiguities regarding the mechanisms of incentives. Second, we applied justice theory to the PHR context. Thereby, we extend the theoretical understanding that has so far been limited to mainly technology acceptance models (Johnson et al. 2014; Lim et al. 2011; Lishan et al. 2009; Maass and Varshney 2012; Moores 2012) and the privacy calculus (Li 2014b; Li et al. 2016). Even though justice theory provides promising impulses for measures firms can take to foster health technology adoption, no previous study has applied a justice theory framework. Overall, our findings support the notions of justice theory that measures of distributive and procedural justice significantly affect privacy concerns and perceived benefits and thus increase PHR adoption (Culnan and Bies 2003). However, we find that financial incentives in terms of monetary compensation and personalization incentives play a different role in the healthcare context. The two incentives affect the adoption of PHR differently, as they correspond to different benefit perceptions. We argue that, personalization incentives contribute to the inherent benefits of PHR usage and thus increase perceived benefits significantly. By contrast, the benefit of monetary compensation is not related to the ultimate purpose of PHRs. Thus, our study emphasizes that the concept of distributive justice is more complex and context dependent than prior research suggests. Third, we assessed actual behavior instead of behavioral intention by conducting a randomized controlled field experiment. As previous literature mainly focused on the behavioral intention (Anderson and Agarwal 2011; Angst and Agarwal 2009; Bansal et al. 2010; Li et al. 2014), evidence on actual adoption is still scarce. Prior research demonstrates a significant gap between attitude or intention and actual behavior (Acquisti et al. 2015; Sheeran 2002). Therefore, the observation of actual behavior provides a key contribution to the discussion of health information technology adoption.

These discussion points raise the question whether the way in which incentives have so far been classified is applicable for all contexts. We propose that it is not the distinction between monetary and non-monetary incentives (e.g. Milne and Gordon 1993) that matters but rather the context relatedness that makes a difference for the effects of organizational measures (Promberger et al. 2012). Whereas financial incentives in terms of monetary compensation can work e.g. for e-commerce settings (Premazzi et al. 2010), we argue that they do not work in contexts, in which the incentivized behavior is not naturally related to a monetary exchange. In the context of our study, financial incentives represent a value that is not related to the ultimate purpose of PHRs. Personalization incentives and fair information practices, by contrast, directly or indirectly increase the inherent value of the PHR. Therefore, our study constitutes a starting point to re-think the conceptualization of incentives for different contexts.

Practical Implications

Our findings yield several practical implications for a variety of PHR providers such as governments, insurers, and employers. The insignificant effect of financial incentives implies that the offer of monetary compensation does not constitute an appropriate strategy to foster PHR disclosure behavior. Our discussion revealed that in contexts of high risks and uncertainty, financial incentives could even provoke reactions against the incentivized behavior (Gneezy et al. 2011; Hoffman et al. 1999). Therefore, we suggest that organizations that are generally associated with high risks in terms of data privacy, such as insurers (Anderson and Agarwal 2011), should avoid financial incentives and focus on other ways to support PHR adoption. Furthermore, we argue that in contrast to settings that naturally involve a monetary exchange, monetary compensation per se plays a subordinate role for data disclosure decisions in healthcare. Individuals decide to use PHRs as they expect a positive impact on their health care. Therefore, we suggest that financial incentives only yield a positive effect on PHR disclosure decisions if they relate to the health care of individuals (e.g. reductions in insurance premiums or price reductions on health services).

In contrast to monetary compensation, personalization incentives constitute a promising way to support PHR adoption rates. Our findings show that personalization incentives significantly increase PHR adoption. In health care, personalization offers unparalleled value. Personalization of health care through digital solutions enhances the efficiency of diagnosis processes, improves communication with health care professionals, and reduces medication errors (Fichman et al. 2011; Reti et al. 2009). A significant advantage of personalization incentives over financial incentives becomes relevant in the long term. Personalization incentives are, in contrast to most financial incentives, of a dynamic nature. The value created by personalized content and services will continue to develop as long as new data input is provided (Gneezy et al. 2011). Therefore, personalization incentives could be particularly effective in influencing the use of PHR platforms in the long term.

Furthermore, fair information practices can significantly increase PHR adoption rates as they provide particular value in the context of sensitive health information. However, PHR providers need to pay attention to the specific way of implementation to benefit from the positive effects. There are several ways to implement fair information practices (Hui et al. 2007). Nevertheless, Awad and Krishnan (2006) argue that only measures that go beyond legal standards will make a difference for the behavioral decisions of individuals. Furthermore, organizations implementing fair information practices to support PHR adoption should be aware of contextual differences (Hui et al. 2007). As discussed above, cultural backgrounds can make a difference for the impact of fair information practices. However, especially for PHR providers in Germany and other countries with cultures of high uncertainty avoidance (Hofstede 1980), the implementation of signals of fair information practices is beneficial.

Limitations and Directions for Future Research

Our study has some limitations that provide opportunities for future research. The German culture has one of the highest uncertainty avoidance values (Hofstede 1980). Therefore, our results are relatively conservative and should hold for cultures characterized by lower uncertainty avoidance as well. However, as prior research has found that cultural backgrounds can have an impact on privacy concerns (Milberg et al. 1995; Milberg et al. 2000), future research should address this topic by examining the impact of cultural backgrounds on PHR adoption decisions. Furthermore, our real-world experimental design implied that only those individuals could be considered who opened the first e-mail and who answered the follow-up study. There are two major arguments, however, that provide an explanation why this sampling bias is not fatal to our study. First, we only excluded a small number of two individuals that registered for POLAVIS VIVA but did not answer the follow-up survey. Second, we conducted the experiment in a real-world setting. Thus, even though we only included those individuals who opened the e-mails, our sample provides valuable implications as it represents the relevant target group. Nevertheless, it is essential to account for this sampling bias when interpreting the results.

PHRs differ in terms of platform features and provider identity. They can be integrated into the patients' existing electronic medical records or they can be standalone systems provided by insurers, employers, governments, or private organizations. Research on PHR adoption has not yet analyzed the effects of PHR type and provider identity. Thus, we see promising opportunities for future research that sheds light on the influence of distributive and procedural justice when the PHR related context factors change (Anderson and Agarwal 2011; Kehr et al. 2015). Furthermore, future research should focus on the provision of data and use of PHRs in the long term. We did not find any significant differences in the number of data released by individuals between the different scenarios of our experiment. This result could mean that the actual decisive step is the decision to register for the PHR platform. Once individuals have decided to opt-in, the amount of data they disclose could play a subordinate role. Therefore, we call for future research that sheds light on this mechanism. Due to limited data access, we were only able to examine data provision within the first two weeks of usage. Since the value of PHR systems mostly arises through long-term use (Assadi and Hassanein 2017; Devaraj and Kohli 2000), future research should conduct longitudinal studies to further examine time effects, as well as other measures, that induce individuals to use PHRs in the long term (Archer et al. 2011; Lester et al. 2016).

Moreover, we found that the different components of justice theory are strongly context dependent. Whereas monetary compensation might incentivize individuals to disclose data in a setting that naturally involves a monetary exchange, they do not work in the PHR context. However, personalization incentives and fair information practices that directly or indirectly relate to the ultimate objective of PHRs do significantly increase PHR adoption. Thus, we propose that future research should re-think the common classifications of e.g. monetary versus non-monetary incentives (Milne and Gordon 1993) and examine the underlying cause-effects relationships of context related versus context un-related incentives. In this regard, a further limitation for the generalizability of our study refers to the implementation of financial incentives, as there are numerous possible ways of implementation (Volpp et al. 2008). We therefore encourage future studies to consider the effects of PHR-related financial incentives such as reductions in insurance premiums or price reductions on healthcare services on PHR adoption.

Conclusion

Despite significant increases in efficiency and cost savings associated with their implementation, the prevalence of PHRs has so far been low. The goal of this study was to shed light on organizational measures that induce individuals to adopt PHR platforms. Drawing on justice theory, we developed a conceptual framework and derived theoretically grounded hypotheses about the impact of financial incentives, personalization incentives, and fair information practices on the adoption of PHR platforms. In cooperation with eHealth ventures, a PHR platform provider in Germany, we conducted a randomized controlled field experiment with 216 participants. The results of our experiment show that the likelihood that individuals register for a PHR platform does not increase with financial incentives. Personalization incentives and fair information practices, by contrast, significantly increase PHR adoption rates by increasing perceived benefits and reducing privacy concerns, respectively. Overall, our results support the notions of justice theory as we showed that measures of both distributive and procedural justice foster PHR adoption. However, we emphasize that the subordinate mechanisms of the effects of distributive and procedural justice on behavioral decisions are more complex and context dependent than prior literature assumed. Therefore, we encourage future researchers to join the discussion and to conduct more nuanced analyses on the effects of context dependency of different incentives.

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