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Influence Factors for Customer Acceptance of Data-Driven Contracts in Insurance Ecosystems

Frederik Seger

Kathrin Figl

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Frederik Seger
University of Innsbruck
Innrain 52, 6020 Innsbruck, Austria
frederik.seger@googlemail.com

Kathrin Figl
University of Innsbruck
Innrain 52, 6020 Innsbruck, Austria
kathrin.figl@uibk.ac.at

Abstract

Datafication offers several benefits to the insurance sector, but the success of data-driven insurance depends very much on customer acceptance. Thus, this study examines factors that influence customer acceptance of data-driven car and health insurance. These two types of data-driven insurance are based on fitness and driving data, both of which require access to sensor and geo-localization data. The results of an online study with 217 participants using advertisements for data-driven insurances showed that highlighting monetary incentives leads to a higher acceptance than highlighting health or safety incentives. Data-driven insurances allow for individualized tariffs, and accordingly, it is more likely that people who rate their driving skills above-average will take out a data-driven car insurance. Privacy concerns are another important influence factor. The findings demonstrate that customer acceptance of data-driven insurance can be influenced to some extent by framing decision-relevant information material.

Keywords: Data-driven insurances, privacy, customer acceptance, above-average effect, framing effects

Introduction

In a world where personal data can be turned into value and a commodity, humans have turned into walking data generators (Bottis and Bouchagiar 2018). Companies are gathering more and more data, which they can take advantage of. In the insurance industry, datafication offers a solution to minimize information asymmetries between insurance and customer. The insurance industry undergoes a tremendous change. Data-driven insurance contracts which gather fitness or driving data of the insured are gaining more and more popularity. One of largest North American life insurers, John Hancock, stated at the end of 2018 that as of 2019, they would only sell interactive life insurance policies, which are also referred to as data-driven insurances. Fitness and health data will be tracked through smartphones and wearables devices, which then can turn into monetary benefits for both involved parties. According to John Hancock, customers are not obliged to share their data. However, they will ultimately pay more than those customers who are willing to share their data (Barlyn 2018). Insurance companies in Germany and Austria are pushing the market of data-driven insurances with a wide variety of offers. Data-driven insurances are considerably new. Nonetheless, it affects many customers. Out of the ten biggest German statutory health insurances, at least three insurances (Techniker Krankenkasse, BARMER, and AOK PLUS) offer data-driven health insurance in July 2019 (AOK PLUS 2019; Barmer 2019; Techniker Krankenkasse 2018). Calculating the number of customers, who have access to data-driven insurances, this currently adds up to almost one-third of all German statutory health insurance customers.

Geo-information data is highly relevant for data-driven health and car insurances. In the context of data-driven health insurances, fitness-apps for instance use location data to be able to track routes when walking, cycling, and jogging, including the altitude meters covered, and make this data available to the insurance company. Data-driven car insurances use global positioning satellite (GPS) technology and sensor data (e.g. accelerometer, gyroscope) to track “vehicle usage and location – including time of day, type of road, and mileage” (Courtney 2013, p. 69) as well as speed to calculate insurance premiums. Information on braking, left-hand-turns, speeding, cornering or harsh steering makes it possible to offer “pay-as-you-drive” premiums that are tailored to the individual driving style and driving habits. In order to identify risk-reducing and risk-increasing driving behavior, data on repeated driving routes can be linked to hazards, crime or accident rates of the geographical locations (Hayward et al. 2019). Geo-positioning data in combination with time data are also necessary to determine driving conditions and exact environmental and weather conditions of the routes (rain, snow, dusk, darkness) for particular locations. Insurers can also use geo-information data to conclude specific insurance contracts for geographical regions, e.g. countries.

Surprisingly, very little is currently known about how this digital disruption in the insurance industry affects customers. The success of an insurance company is strictly dependent on customer acceptance. No matter how beneficial data-driven insurances might be, if customers are not participating or even change the insurance provider due to the presence of a data-driven contract offer, eventually, the downsides exceed the benefits. According to a study by Müller-Peters and Wagner (2017), general customer interest in data-driven insurances is given. The purpose of our research is not only to find out if customers are accepting it, but also whether it is possible to “nudge” customers’ decision to try it out. To this point, there is still uncertainty, which factors influence customer acceptance of data-driven insurances and whether acceptance of data-driven insurance contracts can be influenced via the framing of its incentives and advantages. Based on the theory of reasoned action (Fishbein and Ajzen 1977), this paper aims to identify and examine influencing factors of the customer acceptance of data-driven insurance contracts. In addition, the paper addresses the research question, how customer acceptance of data-driven insurance contracts be influenced. Up to this point, research lacks investigation into how customers react to different framings of data-driven insurances in order to increase acceptance. A variation of presentations of advertisements for data-driven insurance contracts is experimentally tested with an online questionnaire.

From a theoretical perspective, this study contributes to the body of literature by providing the first empirical analysis of relevant influence factors of the customer acceptance of data-driven insurance contracts. From the managerial perspective, it delivers insights for insurances to understand possible influencing factors that can be used to increase customer quantity.

The remainder of this paper proceeds as follows: In the first section, possible influencing factors for the customer acceptance of data-driven insurance contracts are introduced. Next, hypotheses are developed, and the methodology of this study is explained. Then the results of this study are presented before the next section puts them in perspective and discusses their implications. Before a conclusion is drawn, the various limitations that the results come with, are discussed.

Determinants for Customer Acceptance of Data-driven Insurance Policies

This section focuses on attitudes and beliefs that are expected to impact customer acceptance of data-driven insurance policies. The theory of reasoned action developed by Fishbein and Ajzen (1977) gathers insight into how predictions about behavior can be made solely based on attitudes and subjective norms. According to the theory of reasoned action, the attitude towards something is dependent on personal beliefs. These beliefs include the evaluation of specific behavior and the associated consequences that come with this behavior. The behavioral intention of someone is not only dependent on the attitude towards behavior, but also on the subjective norm that this person has, which in turn is based on the normative beliefs and by the motivation to comply with these self-developed norms. Once a behavioral intention is formed, it most likely translates into the actual behavior (Fishbein and Ajzen 1977). In this research, the customer acceptance of data-driven insurance contracts acts as behavioral intention.

One does not decide on the option for its own sake but based on the consequences that come with the decision for this specific choice. For data-driven insurances, the consequence of choosing such a contract may lead, for instance, to monetary incentives. However, customers, who believe that, e.g., health insurance tariffs should be mainly based on solidarity, so that physically fit individuals pay the same amount as people not interested in sports activities, might reject individual monetary advantages. The theory of reasoned action includes beliefs and normative beliefs as relevant influence factors for behavioral intentions. According to Abelson (1979), in belief systems, the elements are not necessarily consensual. Belief systems rely strongly on evaluative and affective components, and there are no boundaries around a belief system. Opinions about something vary extremely between individuals. As the belief influences the behavioral intention (Fishbein and Ajzen 1977), the question arises on how and to what extent belief systems can be affected. Danilov and Lambert-Mogiliansky (2018) suggest that providing new information can modify a person's beliefs and change their behavior in a specific way. In theory, a person's beliefs are fully manipulable (Danilov and Lambert-Mogiliansky 2018). This finding is in line with Akerlof and Shiller (2015), who argue that a change of people's focuses results in the shift in the decisions they make. As a potential method to influence belief systems, we focus in this paper on framing as detailed in the next section.

Framing

When introducing new data-driven insurance contracts, the framing of their advertisement is one major option to influence existing and not yet formed elements of belief systems around data-driven insurances. According to Münscher et al. (2016, p. 514), "framing effects occur when the same (equivalent) information presented in different ways leads to systematically different decisions." One setscrew of framing is the wording and perspective in a communicating text (Tversky and Kahneman 1981). Positive or negative wording can influence one's opinion and actions. For example, in the abortion discussion, a study of Simon and Jerit (2007), significantly changed people's opinion about the ban on abortions, only by using different words: fetus vs. baby.

One might assume that people are vulnerably exposed to framing effects. This is only true to some extent. In a study from De Martino et al. (2006), brain activity from participants was analyzed, and results from the brain scanner suggest that participants were differently affected by framing. The focus of the analysis was on the activity of the prefrontal cortex, which is known to be involved in the planning of action. The more activity on the prefrontal cortex, the more people contemplated what was presented, which resulted in a weaker impact of the framing effect. Overall, although the effect strength varies between participants, no participants were able to equivocate the framing effect (De Martino et al. 2006).

Framing is not a clearly defined concept. The generalizability of much-published research on this effect is problematic and topic-dependent, which makes it necessary to investigate framing effects for data-driven insurances specifically. According to Matthes (2014), there is no coherent theoretical structure about framing, but rather a multitude of different studies that use the concept of framing without deriving it from a unified theory. Past studies focused primarily on the variation of the perspective and individual words (Levin and Gaeth 1988; Tversky and Kahneman 1981). The question arises how these study results can be generalized to the setting of data-driven insurances. In the context of this study, we are interested in a setting where one group reads a text about the positive aspects of the solidarity principle for data-driven insurances and the other group a text of the negative aspects, furthermore we are interested in the effects of either framing the incentives in terms of either monetary or health/safety incentives. Existing information relevant for the decision is presented differently, which shifts the decision-maker's focus. This type of framing method, just described, is called *loose* framing. It is a method of reframing that shapes decision-makers' subjective evaluations of something (Münscher et al. 2016). The opinion is expected to be significantly impacted, as the behavior is influenced by what the reader's attention is drawn to (Kahneman and Thaler 2006).

Solidarity/Fairness

Data-driven insurance contracts partially eliminate the solidarity principle in the insurance industry. Therefore, in this study, we are interested in how a framing manipulation of the solidarity principle influences customer acceptance of data-driven insurance contracts. According to the solidarity principle, better earners, for example, ensure the financing of medical care for financially disadvantaged people and the healthy pay just as much as people with chronic diseases. The status quo bias might lead to a more favorable evaluation of current policies. What already exists is tendentially considered as fair. Therefore, the status quo wants to be sustained (Müller-Peters and Wagner 2017). Data-driven individual tariffs as an alternative can, however, include personal effort to stay healthy or to drive safe, and insurance payments are redistributed accordingly. The question is to what extent opinions can be influenced by a framing that focuses on advantages or disadvantages of the solidarity principle. Kamoen (2012) has shown that positive and negative wording significantly impacts opinions. This leads to the first hypothesis:

H1: *A negative framing of the solidarity principle is positively associated with the customer acceptance of data-driven insurance contracts.*

Incentives

According to the theory of reasoned action (Fishbein and Ajzen 1977), behavioral intention is influenced by beliefs and evaluations. Evaluations mainly focus on the outcome of the choice taken. The customer adoption of a technology or service is highly dependent on the resulting total benefit. In this context, it is the resulting benefit of data-driven insurance incentives. Only if the combined benefits of a new data-driven policy exceed those for the existing policies, a customer will accept it (Rejikumar 2013). The benefits are perceived subjectively differently between the customers (Kortge and Okonkwo 1993). Not only the benefits are taken into account, but also sacrifices are considered, which makes it an individual trade-off (Zeithaml 1988). In the perceived value calculation, for data-driven insurances, an invasion into people's privacy might be perceived as unfavorable. Two significant benefits of data-driven insurance contracts can be seen for individuals. Firstly, monetary advantages can be achieved through individual insurance tariffs. The second benefit is health and safety benefits. For car insurances, it is claimed that lower rates of traffic accidents are associated with an increase in data-driven insurance (British Insurance Brokers' Association (BIBA) 2018) and, for participants of a data-driven insurance policy it is claimed that they live longer than the rest of the insured population (BBC 2018).

However, outcomes in the distant future or with a low certainty are less valued than outcomes with higher certainty and an occurrence in the nearer future (Mazur 1987). Additionally, preventive actions (e.g., health examinations) are not clearly assignable to later positive outcomes. In calculation, this is referred to as hyperbolic discounting. According to hyperbolic discounting, humans discount the value of later rewards (Laibson 1997). In this calculation, a consequence has a timeless value, which is then weighted with the importance of the point in time of the consequences. Looking at incentives for data-driven insurance contracts, monetary savings as well as positive health and safety consequences are pleasant, and the time-preference is positive. It can be assumed that a monetary benefit is far more advantageous than a health benefit. Financial cashbacks occur with high certainty in the near future, if the behavior is in line with the insurance contract policy. Looking at the health gains of a healthy lifestyle, it is evident that the benefits are uncertain and often delayed in time (e.g., increased life span). It is quite different if a monetary incentive for a healthy lifestyle is given (e.g., save up to 30% per year), where the payback is guaranteed and in the near future if the behavior is in line with the insurances policy (Loewenstein et al. 2007). Additionally, Giles et al. (2014) found in their meta-analysis strong evidence that a financial incentive significantly motivates participants for healthy behavior. The just mentioned circumstances in data-driven insurance contracts, give occasion to the following hypothesis:

H2: *A monetary incentive increases customer acceptance of data-driven insurances more than a health (or a safety) incentive.*

The Above-Average Effect

For an individual, data-driven calculation of an insurance policy tariff to be more advantageous to customers than an average tariff, it is a prerequisite that customers are better than others with regard to the relevant criteria and the data used to measure them. Insurance providers might, however, benefit from the "above-average effect" when offering individual data-driven insurance tariffs. The above-average effect is a phenomenon studied by various research psychologists, which found that most humans think of themselves as better than the average, in terms of behavior and characteristics (Alicke and Govorun 2005). This effect can, with marginal differences, be observed in many aspects of life; however, for this paper, only the above-average effect in the sectors of health and driving is relevant. Hoorens and Harris (1998) have, for instance, observed the above-average effect in health behavior. In the self-reported study, participants were asked to evaluate healthy and unhealthy behavior of themselves and their peers. Participants stated that they performed unhealthy behaviors less often and healthy behavior more often than the average participant, both in the past and also in the future. The same self-evaluation can be detected in terms of driving ability. Svenson (1981) conducted a study where American and Swedish participants were asked to rate their driving skills and safety in comparison to other drivers. The results showed that 69% of the Swedish participants and 93% of the American participants had rated their driving skills as above-average. Similar results are observed for the safety level, 77% of the Swedish participants and 88% of the American participants rated themselves as above-average. The existence of an above-average for driving abilities was further demonstrated by McCormick et al. (1986).

As stated before, insurances are getting more and more into the data-driven contract market. As the above-average effect was observed in the health (Hoorens and Harris 1998) and also in the driving sector (McCormick et al. 1986; Svenson 1981), insurances could highly benefit from this phenomenon. The data-driven contracts work in such a way that one gives the insurance data, and as a reward, one gets a cashback or other rewards. The healthier a customer is, or the safer the driving skills of the customer are, the greater the benefits in data-driven insurance contracts; a healthier lifestyle and better driving skills translate into a higher cashback (AachenMünchener; AOK PLUS 2019). The outcome underlies, to some extent, uncertainty. In decisions of uncertain outcomes, people tend to attribute probabilities to different outcomes. So, if, in turn, most people think that their behavior is above-average, it is assumed that they predict a higher reward for themselves, in comparison to the average customer, which results in an even higher perceived incentive to participate in these programs. This increased incentive is expected to influence the behavioral intention in the theory of reasoned action. Therefore, participants who rate themselves as above-average are expected to have a higher perceived incentive in participating in a data-driven contract than participants who rate themselves as below-average. For the mentioned reasons, it is assumable that the following hypotheses hold:

H3: *A person who rates their driving skills (H3a)/health behavior (H3b) higher than those of others has a higher customer acceptance of data-driven car (H3a)/health (H3b) insurance contracts.*

Privacy Concerns

In the process of forming an attitude towards a choice, the negative consequences of a choice need to be judged. In data-driven insurances, consumers might perceive it as a potential negative consequence that highly sensitive data is shared with companies. Metadata has become a widely used currency in order to use free services. This trade-off between free services and privacy stands in direct conflict with the comfort zone of most users (Van Dijck 2014). In internet-delivered electronic services, privacy risks are critical factors for an individual's acceptance (Featherman and Pavlou 2003).

Data privacy in the setting of wearables is widely discussed. Unfortunately, researchers failed to find a common denominator. Lehto and Lehto (2017, p. 250), for instance, reported based on qualitative interviews that for most users, "information collected with wearable devices is not perceived as sensitive or private." They suggested that clear communication of tracked data usage and transparency is mandatory to mitigate privacy concerns (Lehto and Lehto 2017). However, in contrast, the study of Lidynia et al. (2018) suggests that participants preferred to keep fitness tracker data to themselves, as they perceived the data as sensitive and valuable. Yoon et al. (2015) found that the opinion on privacy concerns related to wearables can be divided into two camps: *unnecessary anxiety* and *vague fear*.

In a study by Müller-Peters and Wagner (2017), with 1070 participants, 41% of the participants were, in principle, willing to track their health and deliver the data to the insurance. In this questionnaire, the height of the payback was undefined. 53% were willing to track their health with a fitness wearable device. 12% were even willing to implant a chip beneath the skin to track central somatic functions. Regarding car insurance, 39% were willing to track this information with a plug for the cigar lighter in the vehicle, and 22% were willing to use their smartphone as a gauge. An explanation attempt for the low smartphone acceptance could be the constant tracking of one's location, even when someone is not driving. Additionally, the fear of unintended access to other phone data could be relevant. With a cigar lighter plug, its tracking is only limited to the vehicle. It is tracking in the form of telematics that causes for the majority a feeling of uncomfortableness (Cruickshanks and Waterson 2012). By tracking the driving behavior of people (e.g., driving style, location) using telematics sensors, people are monitored and analyzed. It is the personal attitude towards privacy that defines if this causes a feeling of uncomfortableness or carelessness. As privacy risks are perceived individually, we expect more serious individual concerns to have a negative impact on customer acceptance of data-driven insurances policies. This deduces to the following hypothesis:

H4: *Privacy concerns lower the customer acceptance of data-driven insurances.*

Figure 1 gives an overview of the research model. The model proposes that customer acceptance of a data-driven insurance policy is a function of the framing of advertisement for a data-driven insurance and individual differences such as the above average-effect and privacy concerns. The next section will explain the experimental design and operationalization of variables.

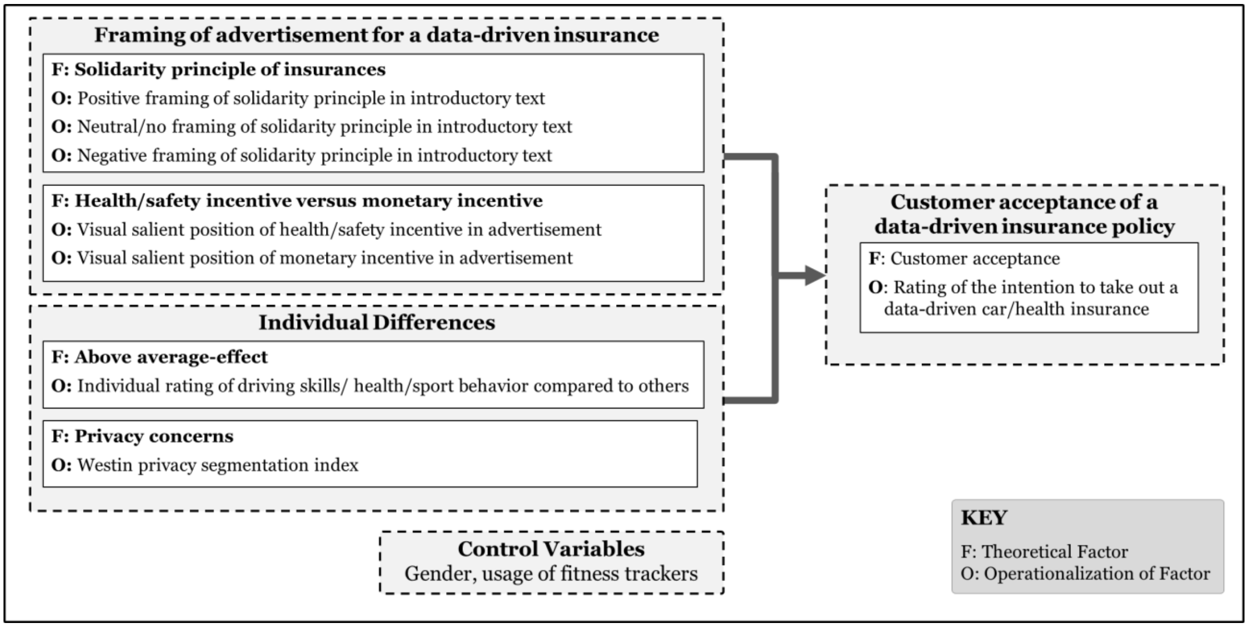

Figure 1. Research Model

Experimental Design and Questionnaire

The study setup is an online questionnaire, which was realized through the website SoSci Survey. We conducted a three (framing of solidarity principle: positively framed vs. negatively framed vs. no framing) × two (framing of incentive: money vs. health/safe driving framing) between-subjects experiment with one dependent variable (intention to take out a data-driven insurance policy).

In total, there are, therefore, six different stimuli combinations. The experimental groups are first differentiated by a positively framed, a negatively framed, and no introductory text about the solidarity principle in the insurance sector. The first scenario is about the significant benefits of the solidarity principle ("Our insurance system has been based on the principle of solidarity...members of a defined community of solidarity provide each other with help and support. True to the motto – One for all, all for one!...The solidarity of the better earners and the healthy secures the financing of medical services and guarantees the fair equal treatment of financially disadvantaged people."). In relation to data-driven contracts, this would be a "loss" framing as the advantages of fairness and solidarity of traditional insurances with equal tariffs are lost/lowered with data-driven contracts. The second introductory text about the solidarity principle is about the drawbacks of the solidarity principle and how data-driven insurance contracts can make insurance premiums more individual and fairer ("a safe driver pays the same contribution as an unsafe driver, and an athletic person pays the same contribution as a couch potato. Recently there has been the possibility of determining an individual and, therefore fair price based on the respective lifestyle."). In the different framings of the solidarity principle, not only individual words are exchanged, as was the case, for example, in the study by Tversky and Kahneman (1981); but the entire perspective varies, similar to the study by Meyerowitz and Chaiken (1987). Overall, a positive and a negative picture of the solidarity principle is created, similar to the study by Lee et al. (2018). Participants in the third scenario do not get an introductory text about the solidarity principle at all, as this is the reference group.

In each of these three experimental scenarios, the groups are split up again. They are differentiated by the advertising incentive (health vs. money), as shown in Figure 2. By providing a different layout of the advertisement, we manipulate the framing of the incentives. Both options are informationally equivalent, but in the "health incentive" experimental group, the sentence about this incentive is positioned in the upper left corner of the advertisement ("Drive up to three times safer through a new car insurance" and "Live up to 13 years longer through a new health insurance"). With the display of different layouts, a shift of location-based visual saliency is expected (Torralba et al. 2006). Zambarbieri et al. (2008, p. 8) note that a reader of online material "starts the exploration almost methodically from left to right and from top to bottom," thus, leading to a visual advantage of the upper left corner of an advertisement.

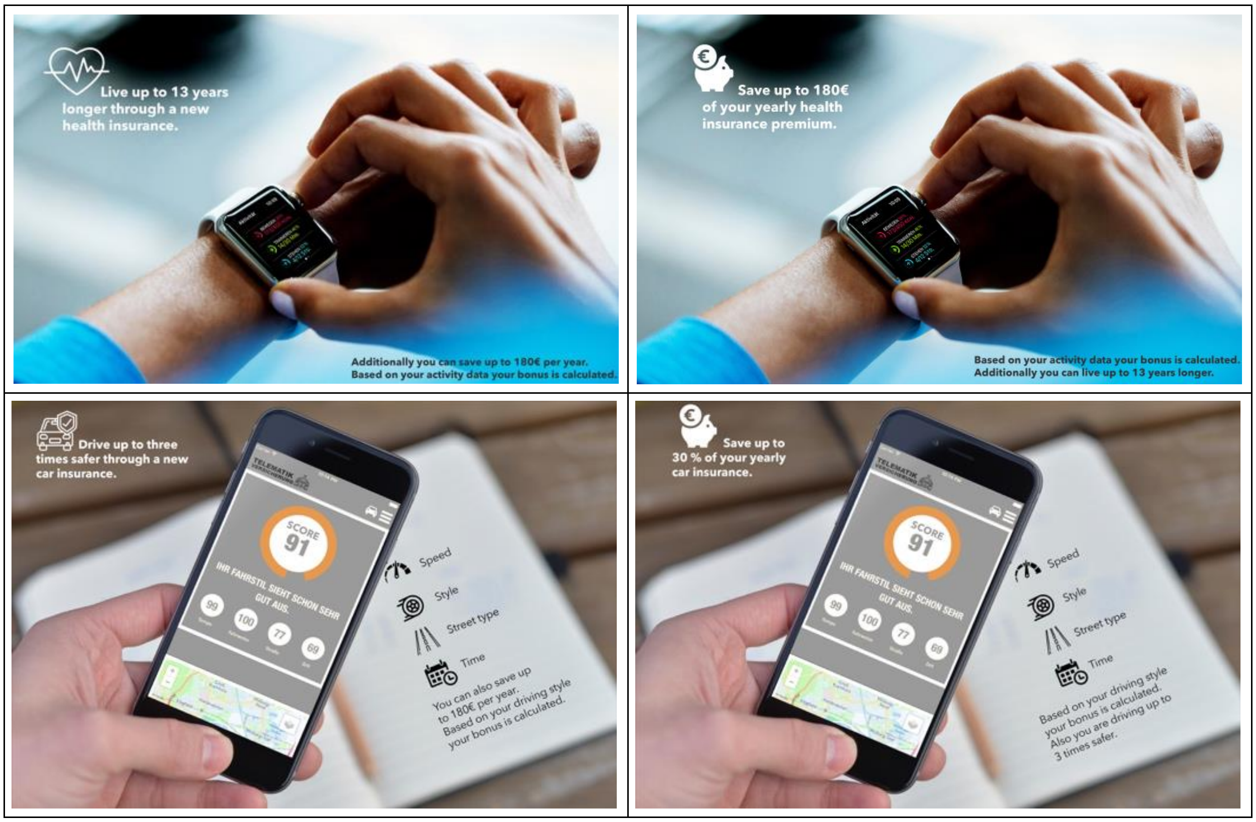

Figure 2. Framing of Incentives (Health vs. Money) for Data-Driven Insurance Contracts

To measure the above-average effect, we let participants rate themselves on their driving-skills, health and sport level on two items each ("Compared to others, how well do you drive a car/how healthy do you live/how athletic are?" and "Compared to you, how well do others drive a car/how athletic are others/how healthy do others live…?") on 7-point Likert-scales (e.g. from worse than others…better than others).

We measure privacy concerns with the Westin Privacy Segmentation Index (Kumaraguru and Cranor 2005), which uses three items (e.g., "Most businesses handle the personal information they collect about consumers in a proper and confidential way.") and a four-point Likert-scale (from "strongly disagree" to "strongly agree"). The Cronbach alpha was 0.70.

The dependent variable customer acceptance of data-driven health insurances ("How likely is it that you would take out a data-driven car/health insurance policy?") is measured on a five-point Likert-scale (from "not at all likely" to "completely likely").

Results

The participants were recruited through the university network. A total of 217 participants were included (56% female), with a mean age of 29 years. Of all participants, 49% were working; the rest were full-time students. Only 19% reported using wearables to track their fitness.

Participants had been assigned randomly to the six different stimuli combinations (experimental groups). We checked for potential differences in several control variables (gender, usage of fitness trackers, opinion on the solidarity principle) between the experimental groups. The tests did not hint on statistically significant differences between experimental groups.

The mean customer acceptance of data-driven health insurance is as low as $M = 2.67$ on a five-point Likert-scale (1 = "not at all likely"; 5 = "completely likely") with a standard deviation of $SD = 1.45$. With the application of the rule that above three is perceived as a high customer acceptance, this translates into an acceptance rate of 36%. The average intention to take out data-driven car insurance value was even lower ($M = 2.51,\ SD = 1.38$). Applying the same rule, the acceptance rate for car insurance is 30%.

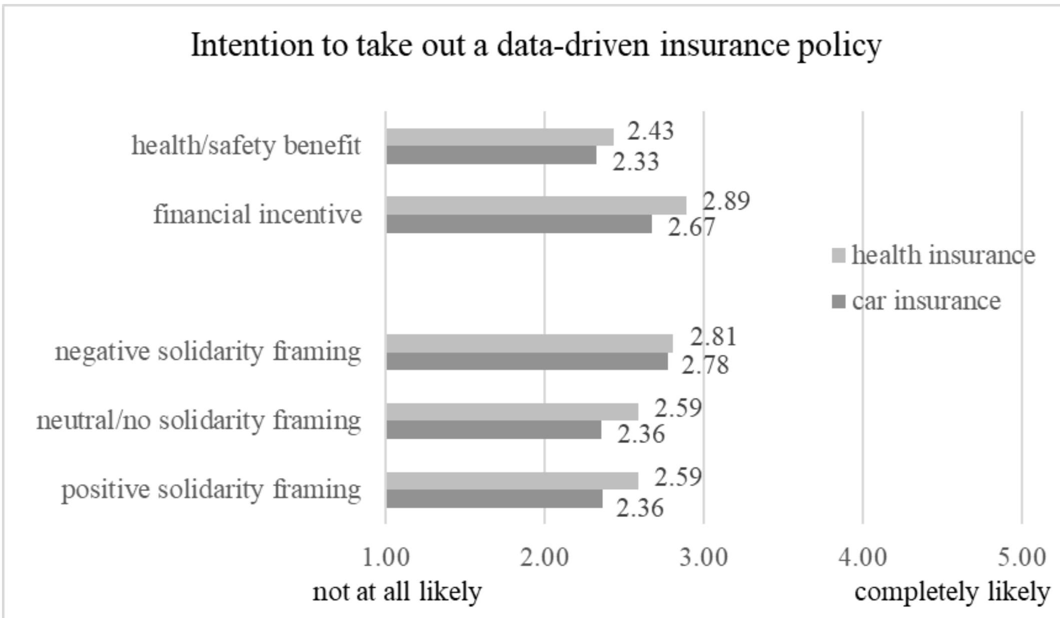

Figure 3. Framing Effects on Customer Acceptance of Data-driven Insurance Contracts

To test our hypotheses, we ran two between-subjects ANOVAs with the intention to take out a data-driven health/car insurance policy as the dependent variables and the framing of solidarity principle and the framing of the incentive as the independent variables and privacy concerns as a covariate. As further covariates, the above-average self-assessments were included (driving skills for car insurance; health, and sport level for health insurance). However, since neither the health nor the sport level had a significant effect on whether to take out a data-driven health insurance policy, they were not included as covariates in the final analysis (H3b rejected).

The results show that the framing of the solidarity principle did not affect the intention to take out a data-driven health insurance policy and only tended to affect the customer acceptance of a data-driven car insurance policy (H1 not supported). A negative framing of the solidarity principle and a focus on the benefit of the individual, and therefore, fair price tended to lead to a higher intention to take out a data-driven car insurance policy. The influence factor with the highest effect size was privacy concerns both for customer acceptance of data-driven car and health insurance policies, with higher privacy concerns leading to lower acceptance (H4 supported). The framing of a monetary incentive of a data-driven insurance policy was more convincing than the framing of a health/safety incentive for both types of insurances (H2 supported). Persons who rated their driving skills higher than those of others have a higher customer acceptance of data-driven car insurance contracts (H3a supported).

Dependent Variable	**Effect**	**F** ($df_{Hypothesis}$=1-2; df_{Error}=212)	**Significance**	**Partial** η^2
Customer acceptance of data-driven health insurance	Framing of the solidarity principle		n.s.	
	Framing of the incentive	6.17	0.01	0.03
	Privacy concerns	35.35	<.001	0.14
Customer acceptance of data-driven car insurance	Framing of the solidarity principle	2.71	0.069	0.03
	Framing of the incentive	4.01	0.046	0.02
	Privacy concerns	23.37	<.001	0.10
	Self-assessed above-average driving skills	12.47	0.001	0.06

Table 1. Results

Regarding specific reasons for not choosing a data-driven insurance policy, we had included further items in the questionnaire. 61% of the participants who did not have a high acceptance of a data-driven insurance policy justified their answers with the fear that they do not know how their data is used.

Discussion

Our results showed a significant effect of privacy concerns on the acceptance of data-driven insurance. Various studies (see e.g., Adjerid et al. 2018; Barth and de Jong 2017) have suggested that in general, people have a high interest in the protection of their privacy, but as it turns out, their actual behavior is not in line with it. This effect is referred to as "privacy paradox." Thus, if a privacy paradox is present in the context of data-driven insurance contracts, privacy concerns would be less influential for actual behavior than for the intended behavior, which we measured in this study. To validate the presence of the privacy paradox, a study setting where the actual behavior is observed would be recommendable for future research.

In both insurance settings, a monetary incentive results in a significantly higher acceptance of data-driven insurance, than a health or safety incentive. Financial cashbacks occur with high certainty in the near future, if the behavior is in line with the insurance contract policy. Looking at the health gains of a healthy lifestyle, it is evident that the benefits are uncertain and often delayed in time (e.g., increased life span). It is quite different if a monetary incentive for a healthy lifestyle is given (e.g., save up to 30% per year), where the payback is guaranteed and in the near future if the behavior is in line with the insurances policy (Loewenstein et al. 2007). In addition, users can take advantage of health and safety benefits by using appropriate third-party applications without using this data in a data-driven contract.

Participants who rated their driving skills as above-average have a significantly higher acceptance than those who rated their driving skills as average or below-average. This can be explained by the perceived incentive of the customer. Those customers, who consider their driving skills as above-average, anticipate a higher bonus, as the yearly paid bonus is based on the driving behavior of the customer, while customers with below-average driving skills might even fear higher costs than with a regular insurance tariff.

A possible explanation for the fact that a negatively framed presentation of the solidarity principle has an effect on acceptance of data-driven car insurance tariffs, whereas it does not for health insurance tariffs, could be that a cautious driving style is more likely to be under one's own control than unforeseen illnesses that cannot be prevented by a healthier lifestyle.

One limitation of the current study is that customer acceptance of data-driven health insurance was not measured fine-granularly, thus for future work we intend to develop a scale to measure the intention to take out data-driven health insurance in detail. Secondly, there is a possible bias in the self-selection of respondents, as we had sent out the invitation to participate in a university mailing list. The generalizability of a student sample is only possible to a limited extent for the total population. On the one hand, students could be sensitized to privacy issues, but on the other hand, they could also be particularly open to trying out new technologies such as fitness trackers. Future work is necessary to examine the generalizability of the results to the total population and/or the customer base for car and health insurances. In the aforementioned setting, participants do not have an actual intention to change something. The intention would be completely different if they are actively browsing the internet to inform themselves about new insurance contracts. Thirdly, as mentioned by Abelson (1979), to make up beliefs, there are no boundaries, and everything that seems relevant for an individual is taken into account. In this questionnaire, participants were only provided with the most basic information about the contract forms. In a real-life setting, it is assumable that participants would gather more information to make up their beliefs, which in fact could influence their opinion in both directions.

Fourthly, a change of the visual saliency in the advertisement, was established by changing the layout of the advertising. The significant results confirmed that the small difference in font size and image detail, in which the incentive was shown, sufficiently changed the visual saliency. Future eye-tracking results could explain in more detail which arguments are considered important in the context of data-driven insurance contracts.

Conclusion

The study set out to test framing effects on acceptance of data-driven insurance contracts. The current results clearly demonstrate the relevance of the investigation of factors influencing customer acceptance of data-driven insurance, as in this specific context, customers seem to be very susceptible to being influenced by different representations of information about the benefits of data-driven insurance contracts.

As shown, privacy is a major issue, and insurance companies need to address customers' data protection concerns in order to reduce fears.

The fact that self-assessed driving skills are a relevant influencing factor for the car insurance industry shows that customers consider various factors when validating the benefits of insurance contracts. A negative framing of the solidarity principle and the emphasis on the benefits of an individually calculated insurance tariff only have a positive effect on customer acceptance in the context of data-driven car insurance; for health insurance, the framing of the solidarity principle was not found to influence customer acceptance significantly.

The advertising incentive also has a significant impact on customer acceptance of data-driven insurance contracts. In both settings, in comparison to a health incentive, a monetary incentive significantly increases acceptance.

The current findings add substantially to our understanding of customers' attitudes and fears towards data-driven insurance contracts by providing first empirical results on factors influencing their acceptance and may assist insurances in designing data-driven tariffs that customers accept and prefer.

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