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Attitudes Towards Personalized Insurance Tariff Models

A Survey Among Students

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Abstract

This paper is based on a survey conducted in 2018 and 2019 among students of a Swiss university of applied sciences, examining the general attitude of young people in Switzerland towards personal data collection by insurance companies as well as towards behavior-based, personalized insurance tariffs in motor vehicle and health insurance. In particular, it identifies perceived benefits and drawbacks of personalized tariffs. It focuses on how much trust young insurance customers have in the personal data collection practices of insurers and other actors in motor and health ecosystems. By analyzing students' feelings about behavior-based insurance, conclusions can be drawn about the potential of digitalization and personalized insurance tariffs.

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1. Introduction

Digitalization offers many new opportunities for the collection and analysis of personal data. Increasingly, for instance, wearables track users' health and behavioral data in order to enhance their levels of fitness and health. The data thus collected are attractive for insurance companies, making it possible to personalize insurance products with behavior-based tariffs. In order to achieve actuarially sound pricing, insurance companies already perform risk classification based on variables that have turned out to be – or are assumed to be – informative with respect to the distribution of claims. Premium levels are often determined by stereotyped variables that describe average risks. For instance, motor insurance is generally more expensive for young males than for other policyholders. The ability to perform an innovative, more precise risk assessment by enabling insurers to identify below-average risks and attract customers by offering lower premiums can thus constitute a significant competitive advantage (Cather, 2018). Further competitive advantage can be generated if an insurer is able to set incentives for risk mitigation. Competition in the insurance industry is fierce, and insurance companies are under considerable pressure to evolve with current trends (Friedman & Canaan, 2017; Eling & Lehmann, 2018). The ubiquitous availability of internet access and the miniaturization of electronic devices have made data collection cheap and simple. Such data are valuable for risk assessment. The GPS location data transmitted by modern cars, for instance, permit accurate conclusions about driving frequency and style (Wüthrich, 2017). By using big data technologies in insurance pricing, insurance companies can thus not only generate a competitive advantage, they can also establish a fine granular risk differentiation system for insurance, which might be perceived as fairer by their customers, in terms of higher risk customers paying more. Data collection and data sharing, however, also raise concerns with respect to data protection and privacy, the threat of surveillance, and potential misuse (Filipova & Welzel, 2010; Gemmo et al., 2017). Furthermore, big data technology may act as a source of discrimination and a catalyst for waiving the solidarity principle advertised in many insurance sectors – such as the basic health insurance scheme ("Grundversicherung") in Switzerland, which is compulsory for all residents (Favaretto et al., 2019; Keller, 2018).

In this paper, we present the results of a survey conducted among students at a Swiss university of applied sciences. We wanted to learn about young people's attitude towards individualized insurance rates and services and about their willingness to share personal data for that purpose. In addition, we sought to establish which institutions or companies are regarded as trustworthy with respect to data collection. We decided to survey young people, for two reasons: First, they have grown up using smartphones and computers, and the collection, sharing, and use of data is an integral part of their social lives. Second, young people are a particularly important group of customers for insurance companies, because customer loyalty is generally high in many branches of insurance (e.g. Suter et al., 2017), with search and switching costs being high compared to potential premium benefits. Since professional experience – as part of a vocational education or at least one year of work experience – is required for the admission to a university of applied sciences in Switzerland, subjects could be expected to have some experience in personal financial matters and at least some financial independence. Our questionnaire dealt with two types of insurance: motor insurance and health insurance. In Switzerland, motor liability insurance is mandatory, whereas partially or fully comprehensive coverage is voluntary. Similarly, basic health insurance is mandatory, with voluntary complementary insurance coverage being quite common. We could therefore expect many of the students surveyed to have given some thought to motor and health insurance. We expected to find differences in the perception of behavior-based tariffs for motor insurance compared to health insurance. While health belongs to the bottom-line concerns of any individual, car ownership and driving are more clearly a lifestyle choice, especially given the wide availability of public transport in Switzerland and the relatively young age of the subjects.

Our paper is organized as follows: In Section 2, we give an overview of recent research on individualized insurance tariffs. We also discuss relevant aspects of the research on people's willingness to disclose or share private data. In Section 3, we try to systemize insurance-relevant data and discuss how the growing availability of data is affecting insurance models. In Section 4, we present the results of our survey, while Section 5 draws some conclusions.

2. State of the Literature

Research has addressed various aspects related to individualized insurance products and services. Demand for insurance has traditionally been explained by rational behavior (Arrow, 1963; Rothschild & Stiglitz, 1976) and later also from a behavioral economics perspective (Kahneman & Tversky, 1979; Thaler, 1980; Kunreuther et al., 2013). In a recent comprehensive study, researchers have found evidence of behavioral biases that prevent consumers from choosing the best offer (Suter et al., 2017).

With new sources of data about the behavior, habits, and lifestyle of individuals becoming available, insurers aim to assess risks in a higher granularity and to offer prices and services that are increasingly individualized. Against this background, actuarial and economically rooted research has been studying how telemonitoring transforms the way health and mobility risks are classified and priced today (McCrea & Farrell, 2018; Weidner et al., 2017; Wüthrich, 2017). In general, the impact of risk classification on insurance market efficiency (Rothschild & Stiglitz, 1976; Schwarze & Wein, 2005) and corresponding regulatory frameworks have been debated (Aseervatham et al., 2016; Schmeiser et al., 2014). Current research on the market impact of digitalization has centered around the effect of adverse selection and cream skimming as a result of mitigated information asymmetry and new risk classification models (Cather, 2018) and, hence, emerging business models due to a shift in the value chain (Eling & Lehmann, 2018). Further topics in the literature are the effects of bonus programs (Henkel et al., 2018), and studies on the use of context-sensitive data for underwriting purposes (Becher, 2016) and for the pricing of health and life insurance contracts (McCrea & Farrell, 2018).

Modern data collection and analytics enable a monitoring of both the extent and the intensity of risk exposure. In motor insurance, this is reflected by usage-based models, namely pay-as-you-drive (PAYD) and pay-how-you-drive (PHYD) insurance (Tselentis et al., 2016). In a PAYD model, the insurance premium is determined by *how long* or *how far* the car is driven – a fact that more closely quantifies the risk the insurer has to bear than simple car ownership. With a PHYD model, the insurance premium depends on figures characterizing the *driving style* such as braking, acceleration, the speed of the car, or mobile phone usage. Tselentis et al. (2016) argued that such pricing schemes reduce cross-subsidies of careful to careless drivers and set incentives that will eventually improve traffic safety.

"Wearables" such as the Apple Watch and other computing devices worn on the body generate large amounts of data on their wearers' physical activity level and lifestyle, which can provide valuable health-related information for the assessment of risks in connection with life, disability, and health insurance (Wiegard & Breitner, 2019). If such data are shared with the insurer, the insurer can incentivize a healthy lifestyle by premium discounts and bonus programs. This results in a "pay-as-you-live" pricing model, where the insurer refunds some of the reduction in claims expenses to the policyholders, rewarding them for risk-mitigating behavior.

The market penetration of personalized insurance products is still low (Dharani et al., 2018). Consumers' concerns about data privacy and protection and their reluctance to share data with an insurance company might still limit demand (Gemmo et al., 2017, p. 28). Also, technology acceptance might vary among different age cohorts and digital affinity.

The decision to disclose private data has traditionally been explained by means of the *privacy calculus* theory, according to which a rational individual agrees to disclose private data if and only if the expected benefit outweighs the expected monetary or non-monetary cost (Culnan & Armstrong, 1999; Kehr et al., 2015). Research, however, has shown that although individuals express objections against sharing data when asked explicitly, they nevertheless *do* share data in certain situations – "users claim to be very concerned about their privacy but do very little to protect their personal data" (Barth & de Jong, 2017, p. 1039). This phenomenon is called the *privacy paradox* (Spiekermann et al., 2001; Kern et al., 2018, p. 5). To explain this phenomenon, some researchers have argued that people take the cost of proper risk assessment into account and refrain from risk assessment if the cost seems to be too high in relation to the perceived risk of data disclosure and privacy loss. If this is true, the decision whether to disclose data would be a boundedly rational one. Others have argued that individuals do not at all perform such a cost–benefit analysis, but rather resort to (possibly wrong) heuristics or focus on the immediate benefits rather than on the long-term cost (Barth & de Jong, 2017). Acquisti et al. (2013) found an “endowment effect,” in that individuals attribute a much higher value to privacy if they are offered a payment for giving it up (“willingness to accept”) than if they have to pay for retaining it (“willingness to pay”).

The survey article by Kern et al. (2018, pp. 5–6) contains a discussion of the literature on experimental results on data sharing. The literature examined in the survey finds that trust and privacy concerns, as well as the *purpose* and the *procedure* of data collection, are key factors in deciding whether or not to disclose private data. The role of personality traits, gender, and social influences, on the other hand, seems to be still unclear. Kehr et al. (2015) found that pre-existing attitudes and dispositions, general institutional trust, as well as the momentary affective state heavily influence how people weigh the risks and benefits of data sharing and are thus crucial for their willingness to disclose private data.

In a pre-study based on hypothetical scenario exercises and a questionnaire, Miesler and Bearth (2016) examined which type of information is relevant for consumers’ willingness to share data. They report that most participants responded negatively when explicitly asked about their willingness to share data. Information about *personal control* and *personal benefits* are particularly relevant for the decision whether to share data, and the willingness to share data seems to be higher in the health sector (with 49% of the participants saying that they are positive towards data sharing) than in the retail or finance sector (19% and 18%, respectively).

According to Rohm and Milne (2004), people seem to consider medical data as particularly sensitive information, raising higher privacy concerns. Of the participants of their survey study, 58% were very concerned about insurance companies using their data, compared to only 43% and 36% when asked about drug stores and grocery stores.

Benndorf and Normann (2018) found that the main factors for the value individuals attribute to privacy are incentives, salience, and transparency. The importance of incentives is reflected in the privacy paradox, in that actual rewards increase the willingness to share. Salience means that the willingness to reveal private data is the lower, the more obvious the sharing is. The authors refer to a study by Tsai et al. (2011), which shows that salience “triggers a preference for […] better privacy policies” (Benndorf and Normann, 2018, p. 1262). Other results, such as Regner and Riener (2017) or Schudy and Utikal (2017), seem to support this finding. Finally, a lack of transparency – if, for instance, it is unclear who will have access to the data and for what purposes – also seems to have a negative effect on individuals’ willingness to disclose private data. In an incentivized experiment conducted by Benndorf and Normann, 10–20 percent of participants (university students) completely refused to disclose private data, while a similar share seemed to be willing to disclose the data almost for free. Those participants who were willing to share demanded about 15 euros for their contact information and 19 euros for their Facebook details to be shared with a German telecommunication company for marketing purposes.

Applications to the insurance industry were studied empirically (Wiegard & Breitner, 2019; Wiegard et al., 2019). By means of expert interviews, as well as an online survey, and employing a privacy calculus approach, Wiegard and his coauthors identified factors that affect the perceived privacy risk and the perceived benefits of pay-as-you-live insurance models. They found information sensitivity and concerns about data misuse by others to be the most influential factors of privacy risk, whereas perceived usefulness and perceived enjoyment were found to be most important for perceived benefit.

3. New Data

With big data, the data landscape for risk assessment has expanded massively, not only with respect to the amount of available data, but also in terms of the type of data available. Traditionally, insurers have based pricing predominantly on static and easily observable variables, which were used for risk classification based on historical claims experiences. Nowadays, data is not only generated by policyholders, but also from insured objects. Together with contextual data, a new data landscape is forming.

Following Arisov et al. (2019, p. 11), we differentiate between four types of data – data about demographics/object characteristics, data about context, data about habits, and data about behavior:

Demographics/object characteristics: While demographics/object characteristics are inherent to the policyholder or the insured object, they exist independently from the behavior of the policyholder or the current state or usage of the insured object. To be useful for risk assessment and pricing, there must be a statistical dependency between the respective variable and the insured loss. There may be, but need not be a clear causal link. Typical examples of variables of this type are age, gender, place of residence, or vehicle type (Gerpott & Berg, 2012, p. 457). The use of such data for insurance pricing has sometimes triggered debate, raising concerns of unfairness or discrimination (see, e.g., Cather, 2018, for the introduction of credit-based insurance scores [CBIS] in the U.S. market for motor insurance in the 1990s).

Context: Context-sensitive data provide information on the risk inherent to a specific situation (Keller & Transchel, 2017). Examples of contextualization are the weather or traffic volume (Husnjak et al., 2015, p. 817). GPS, in combination with publicly available databases for weather and traffic conditions, makes it possible to include context-sensitive information in the evaluation of risk.

Habits: Usage-based data refer to practices that fundamentally determine the risk level. These patterns are influenced by human decisions, but relatively stable in the long run. Typical indicators for motor insurance are usual mileage, type of roads, or time (driving during day or night time) and frequency of use (Dang, 2017, p. 11). Number of steps, or physical activity in general, are similar indicators in the context of health insurance (Wiegard et al., 2019).

Behavior: Behavior-related data provides information about actions that influence a risk at a specific point in time and in a specific situation (Albrecht, 2018, p. 457). Examples are driving speed, braking, and acceleration in the context of motor insurance (Ma et al., 2018) or occasional highly stressful physical activity in the context of health insurance.

These four types of data form a 2x2 matrix (Table 1). One dimension differentiates between more static, permanent, and more dynamic, frequently changing, situation-dependent factors. The second dimension describes the level of control the insured has over the respective risk factor.

Concerning the individualization of insurance tariffs by using data, two aspects play an important role. On the one hand, data differ with respect to their correlation to the risk. Assuming that the available data is evaluated correctly, more accurate data on the actual risk increases the validity of the risk assessment. The finer an insurance product differentiates by underlying risk, the more individualized it is. On the other hand, the frequency of data sharing needs to be considered. The more frequently data is exchanged, the more individualized the products and services can be that are designed as a result. Against this background, we can outline a continuum of individualization ranging from one time to permanent.

Insurance pricing has traditionally been based on socio-demographic risk indicators (age, gender, vehicle type, etc.). Products have a low level of individualization if policyholders are placed in a premium category or price segment based on a single test (e.g., a fitness test) or selected car journeys (Händel et al., 2014, p. 94) for the whole contract term. In contrast to products based on static indicators, these offers include more precise data. The long-term behavior of the insured, however, is not taken into account. The next level of individualized tariffs

	static	dynamic
under relatively little control of insured	demographics/object characteristics	context
under relatively high control of insured	habits	behavior

Table 1. Types of data and their dimensions.

integrates periodically transmitted and/or evaluated average values, or so-called “scores.” These scores are based, for example, on the driving or movement behavior of the policyholder. For the future, insurance products can be expected where risks are assigned to a price–performance segment dynamically based on permanent data transmission.

By considering data about risk factors that the policyholder has control over, the insurer can incentivize the implementation of risk-mitigating measures and thus reduce moral hazard. Further, tracking data has the potential to facilitate proof on occurrence of an insured event.

The potential of big data technologies is, of course, not limited to risk assessment and pricing. Modern data collection and analytics techniques are applied in marketing and in product design. In the terminology of Song et al. (2016, p. 91), modern data analytics technology enables a shift in focus from mere customization of products and services to personalization. If products or services are customized, a user can adapt them to his or her needs him- or herself, by choosing from a variety of options. Personalization goes one step further: Companies can tailor products or services to their customers’ preferences. This requires relatively detailed information about customers, which data collection and analytics methods can increasingly provide.

Furthermore, the possibility of creating additional value through data collection and analysis leverages the rise of business ecosystems, which Panetta (2016) defined as “an interdependent group of actors (i.e., people, things, enterprises) sharing standardized digital platforms to interact with one another to fulfill some commercial or civic purpose.” Ecosystems can offer the customer a “holistic experience” (Avramakis et al., 2019, p. 2). A motor insurance contract, for instance, may be part of a “motor ecosystem,” where the data generated by sensors in the car are not only – and not even predominantly – used for insurance purposes, yet drive all kinds of mobility services. Ecosystems can enable shifting from a “vertical market orientation” to a “customer-centric” one, by offering, for example, insurance policies that adjust “in real-time to accommodate changing needs” (Avramakis et al., 2019, p. 3–4).

These developments – the personalization of services and the rise of ecosystems – are important aspects of big data use in insurance, beyond pricing and risk assessment. First, a simultaneous consideration of these aspects creates a cost advantage by leveraging synergies in data collection and analysis. Second, by increasing the user’s benefit beyond the monetary advantage, insurance companies may increase customer understanding and customer acceptance of behavior-based tariff models, especially if the adoption of such a model requires some effort on the user’s side. Third, insurance companies can position themselves in the ecosystems that their customers will be increasingly accustomed to be surrounded by.

4. Empirical Study

4.1. RESEARCH QUESTION AND SURVEY DESIGN

Our survey was conducted among students at the School of Management and Law and the School of Health Professions of Zurich University of Applied Sciences (ZHAW) between October 2018 and March 2019. The survey was conducted on paper, and the questionnaires were distributed during regular lessons with an explanation that participation was voluntary, and retrieved at the end of the lesson. We distributed about 450 questionnaires and received 286 replies. After removing four mostly empty questionnaires, we ended up with usable responses of 282 students. The response rate was thus about 60%.

The questionnaire we used (see Appendix 7.1) consists of three parts: In the first part, we ask about gender, age, and the relationship between household income and household spending. The second part asks about motor insurance, starting with car ownership. Subjects who did not own a car were directed to skip this part. Part 3 is about health insurance. The questions for motor insurance and health insurance are similar: They aim to elicit individual opinions on data collection and data sharing for behavior-based insurance tariffs, as well as participants' attitudes and expectations with respect to behavior-based tariffs. We wanted to assess the willingness to share data (Questions 2.6, 2.8–2.12 for motor insurance, Questions 3.5–3.9 for health insurance) and learn about common views and values with respect to solidarity and potential discrimination (Questions 2.7, 2.13 for motor insurance, Questions 3.4, 3.10, 3.11 for health insurance). We also wanted to know participants' personal preferences and the benefits expected from individualized insurance tariffs (Questions 2.14–2.16 for motor insurance, Questions 3.12–3.14 for health insurance). In addition, we asked about participants' current insurance cover (Questions 2.3, 2.4, 3.1, 3.2), whether they had heard about individualized motor insurance (Question 2.4), and whether they possessed a mobile health tracking device (Question 3.3). We explicitly asked what they would prefer: an individualized tariff or the traditional model (Questions 2.15 and 3.13).

4.2. DESCRIPTIVE RESULTS

Of the 282 students surveyed, 69% (195 students) were female and 29% (83 students) were male; four students did not answer the gender question (Figure 1). Nearly three quarters of the participants (73%, i.e. 207 students) were between 20 and 24 years old (Figure 2). The mean age was 23.6 years. As to the relationship between household income and spending, 40% reported that they were currently saving money, 27% reported that income and spending were about even, and another 27% said that their spending was exceeding their income (Figure 3).

4.2.1. Motor insurance

26% of the participants (74 students) reported that they own a car. For the second part of the questionnaire, we considered only the answers of these 74 students ("car owners").

Three quarters of the car-owners considered themselves to be careful drivers (fully or mostly, Figure 4). Three quarters of the car owners have partially or fully comprehensive motor insurance coverage (Figure 5). The median annual motor insurance premium reported was in the range of CHF 1,000–1,250 (Figure 6).

58% said that they had already heard of individualized or behavior-related tariffs for motor insurance, whereas 39% said that they had not (Figure 7). Two thirds of the car owners said that careful drivers should benefit from an insurance premium reduction (Figure 9), yet only 43% stated that they were actually willing to share data with the insurance company for the implementation of a behavior-based tariff, while 34% were averse to it (Figure 8).

Asked about the data they would agree to share with their insurer (Figure 10), 81% of the car owners said they would share data about the distances driven. About 65% of the car owners would share information about the types of roads used, and 57% would share data generated in close timely connection to an accident. Between 30% and about half of the car owners would share data about their style of driving, with driver behavior in negotiating bends in the road being the most accepted and speed the least accepted item. Only 12% of the car owners agreed that they would share their geographical position; almost three quarters of car owners were against sharing locational data. These results are consistent with findings by Kehr et al. (2015), where location, speed violations, and time of trip were considered most sensitive, and the car's year of construction and type, as well as distance travelled least sensitive.

With respect to potential advantages of individualized tariffs, about three quarters of the car owners considered the fact that the data collected provided evidence in case of damage to be an advantage, and approximately two thirds saw a potential premium reduction as a benefit for themselves (Figure 11). Fewer, yet still more than 40% of the car owners saw advantages in being motivated to drive more safely or in receiving feedback on their driving style.

A large majority of car owners saw potential problems from insufficient data protection and surveillance (Figure 12). Higher premiums or a misplaced trust in technology were seen as potential disadvantages, each by roughly 40% of the car owners. One third of the car owners saw reduced solidarity as a disadvantage of individualized tariffs. Only about 20% had concerns with respect to the potential discrimination of bad drivers.

While a majority of car owners would allow emergency services to collect driving data (Figure 13), with 60% saying yes and 20% no, the statements for and against this were more evenly matched in the case of insurance companies and car manufacturers, with roughly one third on the "yes" and one third on the "no" side. Support for sharing data with the state, tech companies, or telecommunication providers was generally low, with a majority of car owners opposing such a practice.

About half of the car owners would feel uncomfortable if their driving were tracked (Figure 14). Nearly two thirds of the car owners, however, said that careless drivers should pay higher insurance premiums (Figure 15). A majority of drivers expected to benefit from a behavior-based tariff, and only 16% did not expect to receive a substantial benefit (Figure 16). About half of the car owners would prefer an individualized motor insurance tariff, while another half would prefer the traditional model (Figure 17). The expected premium reduction was moderate, with a skew towards higher reductions (Figure 18).

4.2.2. Health insurance

All participants were asked to answer the questions on health insurance; we therefore consider the answers of all 282 participants.

About half of the participants only has obligatory basic health insurance; the other half has some kind of additional coverage, with percentages decreasing from the less expensive to the more expensive options (Figure 19). The most common deductibles in health insurance are either the minimum amount of CHF 300, which 21% of participants reported to have chosen, or the maximum amount of CHF 2500, which 33% of participants had chosen (Figure 20). Only a quarter of the participants uses a mobile health app (Figure 21).

Opinions on whether a healthy lifestyle should lead to a premium reduction in compulsory health insurance were mixed: While 42% of participants were in favor of such a reduction, 41% were not (Figure 22). Similarly, 50% of the participants would provide health-related data to their insurer in exchange for a premium reduction, whereas 32% would not (Figure 23). While sharing the number of steps walked in day, data provided by a pulse monitor, or number of calories ingested found high acceptance, a majority of participants neither wanted to share data on routes walked nor on amount of sleep. Opposition against sharing locational data was found to be high (Figure 24).

Asked about the potential advantages of individualized health insurance tariffs, a clear majority of the participants considered the possibility of receiving emergency assistance to be an advantage (Figure 25). 54% of the participants saw a premium rebate as a potential advantage, while only 18% did not. With respect to the reduction in healthcare spending, personalized training schedules, and the possibility of comparing their behavior with that of other people, the number of participants who did not consider these points as potential advantages was higher than the number of those who did.

More than three quarters of the participants saw potential problems with data protection and surveillance as potential disadvantages (Figure 26). A majority of the participants had concerns about potential discrimination. About 40 to 50 percent of participants were concerned about reduced solidarity, a misplaced trust in technology, as well as higher premiums.

A majority of the participants would be willing to share data with emergency services (Figure 27). 40 to 50 percent of the participants would share health data with hospitals or with the government. Sharing data with health insurers would be accepted by 31%, yet a relative majority of 41% would prefer not to share data with them. Opposition against sharing health data with other companies, such as pharmaceutical companies, other insurers, or retailers, as well as technology companies or telecommunication providers, was found to be high.

While 33% of the participants said that unhealthy behavior should lead to higher premiums in basic compulsory health insurance, a relative majority of 43% said that it should not (Figure 28). Clear support for higher premiums was apparent only with respect to smoking, where higher premiums were supported by 64% of participants (Figure 29). With respect to alcohol consumption, responses were mixed. With respect to risky sport activities, 30% of the participants felt that they should be a reason for higher premiums, while a majority of 52% were against this.

Most participants would expect a moderate benefit from a behavior-based tariff (Figure 30); 8% stated they would expect to profit considerably, while 5% felt that they would not expect to benefit at all. Accordingly, most participants expected to receive a premium reduction in the medium range (Figure 32). Nevertheless, only 42% of the participants would prefer a behavior-based health insurance tariff, while 55% preferred the traditional model (Figure 31).

4.2.3. Motor vs. health insurance

The second and third parts of our questionnaire were structured similarly, to allow us to find similarities and differences between motor and health insurance. Surprisingly, the participants do not seem to be more reserved with respect to the sharing of health data, compared to driving data – the percentage of those who accepted the idea of data sharing was even slightly higher for health insurance (43% motor vs. 50% health, Questions 2.6/3.5). Price differentiation based on risk-mitigating behavior, however, seems to find more acceptance for motor insurance (65% for motor vs. 42% for health insurance, Questions 2.7/3.4). The answers to Questions 2.13/3.10 indicate the same tendency. While 63% of the participants said that careless drivers should pay higher premiums, only 33% supported a higher premium in case of unhealthy behavior. For motor insurance, the sharing of data related to acceleration, speed driven, and location elicited the strongest opposition. For health insurance, amount of sleep, routes walked, and location were deemed sensitive. In particular, the strong opposition against sharing locational data is striking (Questions 2.8/3.6).

The participants saw some potential for additional value, beyond a premium reduction, in data collection for insurance purposes. At the same time, a premium reduction was seen as a potential advantage by 66% of the participants for motor insurance and by 54% for health insurance (Questions 2.9/3.7). Data protection and surveillance were seen as the main concerns in relation to both motor and health insurance. A premium increase was found to be more of a problem for motor insurance than for health insurance – while discrimination was a greater concern for health insurance (Questions 2.10/3.8).

Participants seem to object to cross-sectional data sharing. While insurance companies and car manufacturers are considered acceptable recipients of driving data, hospitals, government, and health insurance providers have a good chance of being allowed to collect health data. The sharing of driving data with the government, on the other hand, is opposed by many participants (Questions 2.11/3.9). People seem to consider the availability of mobile devices and the data so collected as valuable in case of an emergency or damage, as indicated by the top-ranked answers to Questions 2.9/3.7 (better evidence in case of damage/assistance in case of emergency) and 2.11/3.9 (emergency services as widely accepted recipients of data). The results of our survey, therefore, seem to support corresponding results in the literature, according to which a transparent purpose increases the willingness to share data. The frequency distributions for the expected premium reduction under an individualized tariff are almost similar for motor and for health insurance (Question 2.16/3.14). This might indicate that individuals tend to select an answer somewhere in the middle of the given range because they lack the necessary information to give an educated estimate.

4.3. REGRESSION ANALYSIS

To gain an insight into the impact of gender, age, and the propensity to save with regard to the answers in the second and third parts of our questionnaire, we performed a regression analysis. We used logistic regression for binary questions and cumulative ordered logistic regression for questions with multi-level ordinal scales. In the following, by “significant” we mean significance at the 5% level. The results of the regression analysis are given in Appendix 7.2.

4.3.1. Motor insurance

Performing a regression analysis with gender, age, and propensity to save as independent variables, we found car ownership to be significantly influenced by gender: In the context of our survey, women are less likely to own a car. Next, insurance coverage was found to significantly depend on the propensity to save: Car owners with a higher propensity to save tend to have higher insurance coverage beyond basic liability insurance. There might be different reasons for this: First, people with a higher propensity to save might generally have a higher income and therefore be able to afford more expensive or newer cars, for which more extensive insurance coverage is an economically rational decision. Second, a certain financial strength is required to be able to afford a more extensive insurance coverage. Third, both the propensity to save and the decision to buy comprehensive insurance reflect a prudent character.

Insurance premiums significantly depend on gender and age: In the survey, women and older car owners tended to report lower insurance premiums. If we, in addition, control for insurance coverage, we find that the propensity to save negatively affects insurance premiums, while the insurance coverage has a positive effect on premiums.

According to our findings, male car owners are significantly more likely to know about behavior-based motor insurance tariffs than female car-owners. When looking at the perceived advantages and disadvantages of sharing data, as well as the question as to who car owners would be willing to share data with, we found gender to be significant for the willingness to share data on location, types of road, or speeds driven, which female car owners of our survey we found to be significantly more likely to do than their male counterparts. Women were also found to be significantly less willing to share data with technology companies.

The propensity to save was also found to negatively affect the willingness to share information on the types of road used. Similarly, it appeared to have a negative effect on the willingness to share data with insurance companies and energy providers. People with a higher propensity to save were found to be significantly less likely to think that they would benefit from a behavior-based insurance tariff. Without further information, however, any explanation why this might be is speculative. A sensible hypothesis may be that for people with a greater financial scope, mobility cost is a less important part of the overall budget, and thus the potential monetary benefits, relative to income, are not expected to be sufficiently high to accept the loss of privacy or the effort connected with a behavior-based tariff.

4.3.2. Health insurance

As with motor insurance, we again performed a regression analysis with gender, age, and the propensity to save as independent variables, which revealed the following.

Students with a higher propensity to save tend to have more comprehensive insurance coverage. We did not find any significant impact of the propensity to save on the answers to any other question, which seemed somewhat surprising. A possible explanation might be that many students do not pay for health insurance themselves because their parents agree to pay for their health insurance while they still live at home.

Older participants tended to have higher deductibles and seemed to have significantly more concerns about the possible disadvantages of individualized insurance tariffs, such as the potential discrimination of people with chronic diseases and diminishing solidarity. On the other hand, older participants were found to be significantly more willing to share data with emergency services.

The results of our survey indicate that women are less willing than men to share information on their calorie intake. Women also consider help with chronic diseases, emergency assistance, and savings in terms of a reduction in rates to be less of an advantage than men. In addition, they appear to be more concerned about the potential disadvantages of a misplaced trust in technology and reduced solidarity. Women are also significantly less willing to share health data with tech companies, telecommunication providers, and large retailers. Finally, they stated significantly less often that risky sports should lead to higher basic health insurance premiums.

4.4. FACTOR ANALYSIS

In order to find patterns and possibly identify underlying motives reflected in the answers to our survey, we performed an exploratory factor analysis. We used the principal axis method with varimax rotation, which produces uncorrelated factors. We found seven interpretable factors for the motor insurance part and nine factors for the health insurance part. The factors are listed in Table 1, and the factor loadings on the questions are given in Appendix 7.3.

Scores were calculated using the Ten Berge method. A regression of the factor scores on gender, age, and the propensity to save (Table 4 in Appendix 7.3.3) shows that the coefficient for female gender is significantly positive for MPA1. In the health insurance part, we see a significantly positive coefficient of female gender for HPA6, yet a significantly negative one for HPA3. The coefficient on HPA1 is positive, yet not significantly so (p-value: 0.061). We can speculate that women tend to put more emphasis to the *purpose* of data sharing. The women in our survey group show significantly lower scores for HPA4 and HPA9. Concerns about the sharing of health data seem to increase with the age of the person (negative coefficient of age for HPA5 and HPA6).

To assess the potential impact of the factors on the preference for individualized tariffs, we performed a regression of the preferred tariff (Questions 2.15 and 3.13, respectively) on the factor scores, on expected personal benefit (Questions 2.14 and 3.12), and on familiarity with individualized motor insurance and ownership of a health app, respectively. The results are given in Table 5 in Appendix 7.3.3. For motor insurance, Question 2.14 (expected personal benefit), as well as the factors MPA4 (solidarity concerns) and MPA6 (general willingness to share data) show a coefficient that is significantly different from zero at a 5% level; MPA5 (desire to reward careful behavior) also shows a relatively low p-value (0.057). For health, we see significance for Question 3.12 (expected personal benefits), as well as for *all* factors *except* HPA3 and HPA9. Factor HPA8 (reduction of insurance premiums and healthcare spending) shows the highest value of the coefficient, followed by HPA1 (willingness to share health data for insurance purposes) and HPA2 (desire to reward careful behavior).

It came as no surprise to us that the expected personal benefits emerged as the key motive for the decision to choose an individualized insurance tariff, both for motor and for health insurance. In motor insurance, participants with fewer concerns about data sharing in general seem to prefer an individualized tariff, whereas those with higher concerns about discrimination and a lack of solidarity seem to prefer the traditional model. In health insurance, our factor analysis shows a less clear picture. The expectation of lower premiums seems to be the dominant motive. The willingness to share personal data and self-responsibility also seem to be important.

For motor insurance, it appears that participants do make a distinction between – in terms of Section 3 – “data on habits” and “data on behavior”, at least in motor insurance, as the existence of the two separate factors MPA1, predominantly containing “behavioral” items, and MPA3, predominantly containing “habitual” items, shows. For health insurance, our survey does not show such a distinction, yet this might be a design artifact of the questionnaire used.

Motor	Health
MPA1: Willingness to share driving data for insurance purposes	HPA1: Willingness to share health data for insurance purposes
MPA2: Relaxed attitude with respect to privacy issues	HPA2: Desire for careful behavior to be rewarded
MPA3: Willingness to share driving data in exchange for concrete benefits	HPA3: Willingness to share health data outside the healthcare industry
MPA4: Concerns about a lack of solidarity and discrimination	HPA4: Belief that individualized health insurance tariffs are useful
MPA5: Desire for careful behavior to be rewarded	HPA5: Belief that disadvantages are small
MPA6: General willingness to share data	HPA6: Willingness to share health data with health-related organizations
MPA7: Driving data as evidence in case of an accident	HPA7: Belief that individualized tariffs can be useful in promoting a healthier lifestyle
	HPA8: Belief that health data can reduce insurance premiums and healthcare spending
	HPA9: Unwillingness to collectivize avoidable risks

Table 2. Factors for motor and health. The naming of the factor is based on the authors' interpretation of the factor loadings, which are given in Appendix 7.3.

5. Conclusions

Our study provides insights into the acceptance of behavior-based insurance tariffs based on big data and tracking technologies. With about half of participants saying they would prefer such individualized tariffs to the traditional model, the acceptance of such tariffing models by members of our survey group (i.e. well-educated people born in the 1990s) is quite high – in particular in the light of the privacy paradox, according to which people tend to express a *negative* attitude towards data sharing when asked about their opinion. The survey participants are also relatively open to the use of technology for insurance pricing purposes and obviously see value in the potential of big data and tracking applications for insurance purposes – in particular, in setting incentives for risk mitigation, premium reductions as a reward for risk-mitigating behavior, and other potential services. Data protection and privacy issues are the main concerns. Our participants are reluctant to share their data with technology or telecommunication companies. We found this to be surprising, considering that these companies could be said to already possess much of the relevant data anyway, even though many people may not be aware of that.

With respect to motor insurance, our survey shows a lower willingness to share data concerning detailed driving behavior. In contrast to locational data, which our participants clearly do not wish to share, our results provide no evidence that the data generated by health tracking devices is considered to be particularly sensitive. How this relates to the results of Rohm and Milne (2004), according to which medical data is particularly sensitive, with a majority of people being reluctant to share it with insurance companies, is unclear. One might argue that the perception of data sharing has changed over the last 15 years, with people having become accustomed to the presence of mobile electronic devices. It could also be argued that health tracking data is perceived more as lifestyle data than as medical data. Another argument could be a lack of negative experiences with mobile applications in the context of insurance.

Since the acceptance of behavior-based tariffs seems to decrease with increasing personal financial strength, monetary aspects such as the size of the potential premium reduction relative to the household income may play an important role in people's data sharing decisions. The insurance products considered in our survey – motor and health insurance – are relatively expensive, compared to other insurance products such as household or liability insurance. It is not clear yet how the results of our survey translate to other branches of insurance. Since data sharing and tracking (or being tracked) may cause unease, insurers must assess carefully whether the potential gains outweigh potential customer dissatisfaction. The result of customers' cost–benefit analysis will probably depend on the absolute price of the insurance product in question. Insurers could also try to reduce the privacy cost of their products; on-board analytical devices, for instance, may find greater acceptance than the transmission of raw data over the internet and server-based analyses if the devices are sufficiently transparent.

While many aspects of data sharing are still under research and the results are sometimes contradictory, some patterns are emerging from the recent research literature. The decision to share data often seems to be made either under bounded rationality or somewhat irrationally, and personal opinions and concerns, as well as framing effects appear to play an important role. Incentive, salience, and transparency are important determinants for the willingness to disclose private data. In particular, people want companies to demonstrate a clear purpose for the collection of personal data, and they expect a reward for disclosing their data. Since social norms and situational settings play an important role, technological changes (e.g., new technical devices) may trigger changes in consumers' preferences and, thus, in their decisions.

These effects will be decisive for the design of behavior-based insurance products if they are to meet wide-spread acceptance.

6. References

Acquisti, A., John, L. K., & Loewenstein, G. (2013). What is privacy worth? *Journal of Legal Studies 42*(2), 249–274.

Albrecht, P. (2018). Tarifierung in der Privatversicherung: Big Data, Risikoadäquanz, Solidarität. *Zeitschrift für die gesamte Versicherungswissenschaft 107*(5), 449–467.

Arrow, K. J. (1963). Uncertainty and the welfare economics of medical care. *American Economic Review 53*(5), 941–973.

Arisov, E., Becker, J. G., Erny, M., & Zeier Röschmann, A. (2019). *Individualisierte Versicherungslösungen in einer digitalen Welt* [Studie]. Zentrum für Risk & Insurance der ZHAW School of Management and Law, Zurich University of Applied Sciences.

Aseervatham, V., Lex, C., & Spindler, M. (2016). How do unisex rating regulations affect gender differences in insurance premiums? *Geneva Papers on Risk and Insurance: Issues and Practice 41*(1), 128–160.

Avramakis, E., Anchen, J., & Raverkar, A. K. (2019). *Digital ecosystems: extending the boundaries of value creation in insurance.* Swiss Re Institute.

Barth, S., & de Jong, M. D. T. (2017). The privacy paradox – investigating discrepancies between expressed privacy concerns and actual online behavior – a systematic literature review. *Telematics and Informatics 34*(7), 1038–1058.

Becher, S. (2016). Wearables – a new chance for private insurance companies from the underwriting view. *Zeitschrift für die gesamte Versicherungswissenschaft 105*(5), 563–565.

Benndorf, V., & Normann, H.-T. (2018). The willingness to sell personal data. *Scandinavian Journal of Economics 120*(4), 1260–1278.

Cather, D. A. (2018). Cream skimming: innovations in insurance risk classification and adverse selection. *Risk Management and Insurance Review 21*(2), 335–366.

Culnan, M. J., & Armstrong, P. K. (1999). Information privacy concerns, procedural fairness, and impersonal trust: an empirical investigation. *Organization Science 10*(1), 104–115.

Dang, J. (2017). *Unveiling the full potential of telematics.* Swiss Reinsurance Company.

Dharani, S., Isherwood, T., Mattone, D., & Moretti, P. (2018, April). Telematics: poised for strong global growth. *McKinsey Insights.* https://www.mckinsey.com/industries/automotive-and-assembly/our-insights/telematics-poised-for-strong-global-growth (2019/05/27).

Eling, M., & Lehmann, M. (2018). The impact of digitalization on the insurance value chain and the insurability of risks. *Geneva Papers on Risk and Insurance: Issues and Practice 43*(3), 359–396.

Favaretto, M., De Clercq, E., & Elger, B. S. (2019). Big Data and discrimination: perils, promises and solutions. A systematic review. *Journal of Big Data 6*(12).

Filipova, L., & Welzel, P. (2010). Reducing asymmetric information in insurance markets: cars with black boxes. *Telematics and Informatics 27*(4), 394–403.

Friedman, S., & Canaan, M. (2017). Growth options: insurers can capitalize on connectivity, digitalization. In S. Friedman & M. Canaan, *2018 insurance outlook: shifting strategies to compete in a cutting-edge future* [Report] (pp. 4–9). Deloitte Center for Financial Services.

Gemmo, I., Browne, M. J., & Gründl, H. (2017). *Transparency aversion and insurance market equilibria* [ICIR Working Paper No. 25/17]. International Center for Insurance Regulation, University of Frankfurt.

Gerpott, T. J., & Berg, S. (2012). Präferenzen für Pay-As-You-Drive-Versicherungsmerkmale bei Privatkunden – Eine conjoint-analytische Untersuchung. *Schmalenbachs Zeitschrift für betriebswirtschaftliche Forschung 64*(4), 456–492.

Händel, P., Ohlsson, J., Ohlsson, M., Skog, I., & Nygren, E. (2014). Smartphone-based measurement systems for road vehicle traffic monitoring and usage-based insurance. *IEEE Systems Journal 8*(4), 1238–1248.

Henkel, M., Heck, T., & Göretz, J. (2018). Rewarding fitness tracking. The communication and promotion of health insurers' bonus programs and the use of self-tracking data. In G. Meiselwitz (Ed.), *Social Computing and Social Media. Technologies and Analytics. 10th Internat. Conference SCSM 2018 Proceedings, Part II* (pp. 28–49). Springer.

Husnjak, S., Peraković, D., Forenbacher, I., & Mumdziev, M. (2015). Telematics system in usage based motor insurance. *Procedia Engineering 100*, 816–825.

Kahneman, D., & Tversky, A. (1979). Prospect theory: an analysis of decision under risk. *Econometrica 47*(2), 263–291.

Kehr, F., Kowatsch, T., Wentzel, D., & Fleisch, E. (2015). Blissfully ignorant: the effects of general privacy concerns, general institutional trust, and affect in the privacy calculus. *Information Systems Journal 25*(6), 607–635.

Keller, A. & Transchel, F. (2017). *Telematics: connecting the dots. Swiss Re telematics solutions for better risks and fairer premiums* [Report]. Swiss Re.

Keller, B. (2018, March). *Big data and insurance: implications for innovation, competition and privacy* [Report]. The Geneva Association.

Kern, J., Fabian, B., & Ermakova, T. (2018). *Experimental privacy studies – an initial review of the literature* [Working Paper]. Humboldt University of Berlin and University of Potsdam. https://ssrn.com/abstract=3171929 or http://dx.doi.org/10.2139/ssrn.3171929

Kunreuther, H. C., Pauly, M. V., & McMorrow, S. (2013). *Insurance and Behavioral Economics: Improving Decisions in the Most Misunderstood Industry*. Cambridge University Press.

Ma, Y.-L., Zhu, X., Hu, X., & Chiu, Y.-C. (2018). The use of context-sensitive insurance telematics data in auto insurance rate making. *Transportation Research Part A 113*, 243–258.

McCrea, Michael, & Farrell, Mark (2018). A conceptual model for pricing health and life insurance using wearable technology. *Risk Management and Insurance Review* **21**(3), pp. 389–411.

Miesler, L., & Bearth, A. (2016). „Willingness to share" im Kontext Big Data: Wie entscheiden Kunden, ob sie ihre persönlichen Daten mit Unternehmen teilen? In Deutscher Dialogmarketing Verband e.V. (Ed.). *Dialogmarketing Perspektiven 2015/2016. Tagungsband 10. wissenschaftlicher interdisziplinärer Kongress für Dialogmarketing* (pp. 49–66). Springer Gabler.

Panetta, K. (2016, October 17). Ecosystems drive digital growth [Web article]. *Smarter with Gartner.* https://www.gartner.com/smarterwithgartner/ecosystems-drive-digital-growth/ (2019/05/19).

Regner, T., & Riener, G. (2017). Privacy is precious: on the attempt to lift anonymity on the internet to increase revenue. *Journal of Economics and Management Strategy 26*(2), 318–336.

Rohm, A. J., & Milne, G. R. (2004). Just what the doctor ordered: the role of information sensitivity and trust in reducing medical information privacy concern. *Journal of Business Research 57*(9), 1000–1011.

Rothschild, M., & Stiglitz, J. (1976). Equilibrium in competitive insurance markets: an essay on the economics of imperfect information. *Quarterly Journal of Economics 90*(4), 629–649.

Schmeiser, H., Störmer, T., & Wagner, J. (2014). Unisex insurance pricing: consumers' perception and market implications. *Geneva Papers on Risk and Insurance: Issues and Practice 39*(2), 322–350.

Schudy, S., & Utikal, V. (2017). "You must not know about me" – on the willingness to share personal data. *Journal of Economic Behavior and Organization 141*, 1–13.

Schwarze, R., & Wein, T. (2005). Is the market classification of risk always efficient? Evidence from German third party motor insurance. *German Risk and Insurance Review 1*(4), 173–202.

Song, J. H., Kim, H. Y., Kim, S., Lee, S. W., & Lee, J.-H. (2016). Effects of personalized e-mail messages on privacy risk: moderating roles of control and intimacy. *Marketing Letters 27*(1), 89–101.

Spiekermann, S., Grossklags, J., & Berendt, B. (2001). E-privacy in 2nd generation e-commerce: privacy preferences versus actual behavior. In M. P. Wellman, Y. Shoham. *Proceedings of the 3rd ACM conference on Electronic Commerce* (pp. 38–47). ACM.

Suter, J., Duke, C., Harms, A., Joshi, A., Rzepecka, J., Lechardoy, L., Hausemer, P., Wilhelm, C., Dekeulenaer, F., & Lucica, E. (2017, May). *Study on consumers' decision making in insurance services: a behavioural economics perspective* [Final report]. Publications Office of the European Union.

Thaler, R. (1980). Toward a positive theory of consumer choice. *Journal of Economic Behavior and Organization 1*(1), 39–60.

Tsai, J. Y., Egelman, S., Cranor, L., & Acquisti, A. (2011). The effect of online privacy information on purchasing behavior: an experimental study. *Information Systems Research 22*(2), 254–268.

Tselentis, D. I., Yannis, G., & Vlahogianni, E. I. (2016). Innovative insurance schemes: pay as/how you drive. *Transportation Research Procedia 14*, 362–371.

Weidner, W., Transchel, F. W. G., & Weidner, R. (2017). Telematic driving profile classification in car insurance pricing. *Annals of Actuarial Science 11*(2), 213–236.

Wiegard, R., & Breitner, M. H. (2019). Smart services in healthcare: a risk–benefit analysis of pay-as-you-live services from customer perspective in Germany. *Electronic Markets 29*(1), 107–123.

Wiegard, R., Guhr, N., Krylow, S., & Breitner, M. H. (2019). Analysis of wearable technologies' usage for pay-as-you-live tariffs: recommendations for insurance companies. *Zeitschrift für die gesamte Versicherungswissenschaft 108*(1), 63–88.

Wüthrich, M. V. (2017). Covariate selection from car telematics driving data. *European Actuarial Journal 7*(1), 89–108.

7. Appendix

7.1. QUESTIONNAIRE

Our survey was conducted in German and the questionnaire was translated into English for this paper. The possible answers are given in parentheses below. “5L X/Y” means that a 5-point Likert scale from X to Y was given for the answers.

ZHAW [Zurich University of Applied Sciences] is performing a study on “individualized insurance premiums” for motor and health insurance. With new technologies (GPS, trackers, apps etc.), data can be collected, and insurance tailored to the individual behavior. We are examining such models with respect to acceptance, trust, and benefit.

[Technical instructions on how to fill in the questionnaire.]

1. General questions

[1.1] Gender (male/female)
[1.2] Age
[1.3] What is the relationship between income and spending in your household? (saving money/about even/spending more/do not know/no answer)

2. Motor insurance

[2.1] Do you own a car? (yes/no [if no, then continue to 3.])
[2.2] Do you consider yourself to be a careful driver?
[2.3] What insurance coverage do you currently have? (liability/partial coverage/full coverage/do not know)
[2.4] What is your annual premium for motor insurance? (in CHF, <500, 500 to 750, 750 to 1000, 1000 to 1250, 1250 to 1500, 1500 to 1750, 1750 to 2000, >2000)
[2.5] Have you heard of individualized or behavior-based motor insurance (based on trip recorders or GPS trackers)? (yes/no)
[2.6] Would you share data with your insurance company for the calculation of a behavior-based insurance tariff? (5L yes/no)
[2.7] Should careful drivers benefit from a premium reduction? (5L yes/no)
[2.8] Which data about your driving style would you be willing to share with your insurer? (5L yes/no for each item)
  [2.8.1] Distance driven
  [2.8.2] Location (GPS-based)
  [2.8.3] Time of car usage
  [2.8.4] Using highways, rural or city roads
  [2.8.5] Speed driven
  [2.8.6] Acceleration
  [2.8.7] Braking
  [2.8.8] Behavior in negotiating bends
  [2.8.9] Distance to other vehicles
  [2.8.10] Driving behavior 20 seconds before and 10 seconds after an accident
[2.9] How great, from your perspective, are the advantages for the customer that may result from an individualized motor insurance tariff? (5L very high/very low for each item)
  [2.9.1] Feedback on driving behavior
  [2.9.2] Premium reduction
  [2.9.3] Better evidence in case of damage
  [2.9.4] Better assessment of fairness of premium
  [2.9.5] Additional services (e.g., assistance in case of an accident)

[2.9.6] Motivation for me to drive more safely

[2.10] How severe are, from your perspective, the disadvantages for the customer that may result from an individualized motor insurance tariff? (5L very high/very low for each item)

[2.10.1] Problems with data protection

[2.10.2] Higher premiums

[2.10.3] Surveillance

[2.10.4] Misplaced trust in technology

[2.10.5] Discrimination of bad drivers

[2.10.6] Reduced solidarity

[2.11] Whom would you allow to collect data on your driving style? (5L yes/no for each item)

[2.11.1] Car manufacturers

[2.11.2] Government

[2.11.3] Emergency services (police, ambulance, etc.)

[2.11.4] Tech companies

[2.11.5] Insurance companies

[2.11.6] Energy suppliers

[2.11.7] Telecommunication providers

[2.12] To what extent would you feel uncomfortable with your driving being tracked?
(5L very uncomfortable/not uncomfortable at all)

[2.13] Should careless drivers pay higher motor insurance premiums? (5L yes/no)

[2.14] To what extent would you, in your opinion, benefit from a behavior-based insurance tariff? (5L extremely/not at all)

[2.15] Would you prefer individualized over traditional insurance? (individualized insurance/traditional insurance)

[2.16] Given your driving style, what premium reduction in motor insurance would you expect to receive?
(0%/5%/10%/15%/20%)

3. Health insurance

[3.1] What type of health insurance do you currently have? (mandatory basic health insurance/supplementary outpatient insurance/partial supplementary hospital insurance/full supplementary hospital insurance)

[3.2] What is currently your deductible for your basic health insurance?
(CHF 300/500/1000/1500/2000/2500)

[3.3] Do you use a mobile health app (step counter, pulse monitor, etc.) or a fitness tracker/smart watch? (yes/no)

[3.4] Should people be granted a premium reduction for their compulsory health insurance if they can prove, by means of a mobile health-app or a fitness tracker, that they have a healthy lifestyle? (5L yes/no)

[3.5] Would you be prepared to provide data on your health-related behavior to benefit from a premium reduction for your basic health insurance? (5L yes/no)

[3.6] What data would you be willing to share with your insurer in exchange for a premium reduction? (5L yes/no)

[3.6.1] Steps walked

[3.6.2] Routes walked

[3.6.3] Data of a pulse monitor

[3.6.4] Calorie intake

[3.6.5] Amount of sleep

[3.6.6] Location

[3.7] How great, from your perspective, would be the advantages of an individualized health insurance tariff?
(5L very high/very low)

[3.7.1] Personalized health advice

[3.7.2] Personalized training schedule

[3.7.3] Comparison with others

[3.7.4] Reminders about medication schedule

[3.7.5] Help with chronic illness

[3.7.6] Emergency assistance

[3.7.7] Rebate for health insurance premium
[3.7.8] Reduction of my healthcare costs

[3.8] How great, from your perspective, are the disadvantages of an individualized health insurance tariff for the customer? (5L very high/very low)
[3.8.1] Problems with data protection
[3.8.2] Higher premiums
[3.8.3] Surveillance
[3.8.4] Misplaced trust in technology
[3.8.5] Discrimination of people suffering from chronic illnesses
[3.8.6] Reduced solidarity

[3.9] Whom would you allow to collect data on your health-related behavior? (5L yes/no)
[3.9.1] Government
[3.9.2] Hospitals
[3.9.3] Pharmaceutical companies
[3.9.4] Health insurance companies
[3.9.5] Other insurance companies
[3.9.6] Emergency services
[3.9.7] Tech companies
[3.9.8] Telecommunication providers
[3.9.9] Large retailers

[3.10] Should unhealthy behavior result in a higher premium for basic health insurance? (5L yes/no)

[3.11] What type of behavior should lead to a higher premium for basic health insurance? (5L yes/no)
[3.11.1] Smoking
[3.11.2] Alcohol consumption
[3.11.3] Workaholism
[3.11.4] Risky sport activities
[3.11.5] Meat consumption
[3.11.6] Sugar consumption

[3.12] To what extent would you, in your opinion, benefit from a behavior-based tariff? (5L extremely/not at all)

[3.13] Would you prefer a behavior-based or a traditional health insurance tariff? (behavior-based/traditional)

[3.14] Given your lifestyle, what premium reduction for your health insurance would you expect to receive? (0%/5%/10%/15%/20%)

7.2. REGRESSION

7.2.1. Motor insurance

		Gender				Age				Propensity to save			
		β	s	p		β	s	p		β	s	p	
[2.1]	log	-1.001	0.292	0.001	***	0.073	0.040	0.071		0.176	0.152	0.248	
[2.2]	cum	0.157	0.468	0.738		0.021	0.065	0.746		-0.123	0.211	0.562	
[2.3]	cum	-0.707	0.506	0.162		-0.108	0.062	0.084		0.792	0.253	0.002	***
[2.4]	cum	-1.432	0.501	0.004	***	-0.182	0.059	0.002	***	-0.147	0.217	0.497	
[2.5]	log	-1.491	0.579	0.010	*	-0.102	0.068	0.138		-0.358	0.272	0.188	
[2.6]	cum	0.081	0.439	0.854		0.073	0.060	0.226		-0.252	0.194	0.194	
[2.7]	cum	-0.435	0.469	0.354		-0.024	0.059	0.680		-0.110	0.201	0.584	
[2.8.1]	cum	0.484	0.539	0.369		0.083	0.073	0.259		-0.429	0.284	0.131	
[2.8.2]	cum	1.014	0.476	0.033	*	0.065	0.065	0.314		-0.021	0.207	0.920	
[2.8.3]	cum	0.040	0.447	0.928		0.097	0.064	0.127		-0.155	0.192	0.421	
[2.8.4]	cum	-0.146	0.471	0.757		0.107	0.074	0.149		-0.742	0.251	0.003	***
[2.8.5]	cum	0.959	0.464	0.039	*	0.122	0.064	0.055		-0.396	0.210	0.059	
[2.8.6]	cum	0.658	0.461	0.154		0.121	0.064	0.057		-0.374	0.211	0.076	
[2.8.7]	cum	0.941	0.464	0.042	*	0.103	0.063	0.105		-0.400	0.207	0.054	
[2.8.8]	cum	0.671	0.459	0.144		0.110	0.064	0.085		-0.346	0.207	0.095	
[2.8.9]	cum	0.784	0.451	0.082		0.113	0.062	0.069		-0.186	0.195	0.340	
[2.8.10]	cum	-0.601	0.479	0.209		0.122	0.065	0.060		-0.052	0.207	0.803	
[2.9.1]	cum	-0.006	0.443	0.990		0.035	0.061	0.569		-0.119	0.198	0.549	
[2.9.2]	cum	-0.440	0.459	0.338		0.045	0.063	0.470		0.115	0.211	0.585	
[2.9.3]	cum	-0.659	0.483	0.172		0.106	0.072	0.139		-0.270	0.220	0.219	
[2.9.4]	cum	-0.669	0.468	0.153		0.007	0.064	0.916		-0.023	0.210	0.913	
[2.9.5]	cum	-0.606	0.458	0.186		0.024	0.063	0.699		-0.013	0.207	0.951	
[2.9.6]	cum	0.330	0.449	0.462		0.088	0.067	0.190		-0.080	0.194	0.678	
[2.10.1]	cum	0.066	0.485	0.891		0.035	0.069	0.610		-0.139	0.220	0.525	
[2.10.2]	cum	-0.695	0.466	0.136		-0.087	0.064	0.170		0.055	0.215	0.797	
[2.10.3]	cum	0.015	0.479	0.975		0.000	0.064	0.994		-0.209	0.222	0.346	
[2.10.4]	cum	-0.138	0.453	0.761		0.059	0.060	0.325		0.366	0.206	0.076	
[2.10.5]	cum	0.594	0.468	0.204		0.021	0.062	0.736		0.170	0.206	0.411	
[2.10.6]	cum	0.463	0.472	0.326		-0.004	0.065	0.954		0.402	0.209	0.054	
[2.11.1]	cum	-0.412	0.448	0.357		0.073	0.067	0.278		-0.308	0.206	0.135	
[2.11.2]	cum	0.312	0.447	0.486		0.058	0.063	0.358		-0.103	0.207	0.621	
[2.11.3]	cum	-0.015	0.449	0.973		-0.028	0.060	0.640		-0.154	0.197	0.434	
[2.11.4]	cum	-0.953	0.476	0.045	*	0.037	0.070	0.601		-0.064	0.215	0.768	
[2.11.5]	cum	0.272	0.448	0.543		0.119	0.062	0.056		-0.461	0.200	0.021	*
[2.11.6]	cum	0.310	0.451	0.492		0.111	0.068	0.103		-0.453	0.211	0.031	*
[2.11.7]	cum	-0.750	0.472	0.112		0.069	0.069	0.323		-0.132	0.213	0.536	
[2.12]	cum	0.503	0.439	0.252		-0.037	0.059	0.528		0.311	0.193	0.107	
[2.13]	cum	-0.197	0.454	0.665		0.057	0.057	0.314		-0.016	0.201	0.938	
[2.14]	cum	-0.321	0.464	0.490		0.017	0.059	0.778		-0.445	0.222	0.045	*
[2.15]	log	-0.926	0.538	0.085		-0.010	0.065	0.881		-0.511	0.261	0.050	
[2.16]	cum	-0.254	0.465	0.585		-0.002	0.057	0.968		-0.290	0.228	0.204	

Table 3. Results of a regression of gender (0 = male, 1 = female), age, and propensity to save on the answers in the "motor insurance" part of the survey. For questions with two options, a logistic regression (log), for questions with more than two options, a cumulative logistic regression (cum) was performed.

7.2.2. Health insurance

		Gender				Age				Propensity to save			
		β	s	p		β	s	p		β	s	p	
[3.1]	cum	-0.413	0.262	0.115		-0.066	0.037	0.078		0.241	0.119	0.044	*
[3.2]	cum	0.084	0.251	0.739		0.093	0.040	0.020	*	-0.169	0.124	0.171	
[3.3]	log	0.250	0.323	0.440		0.012	0.043	0.783		0.165	0.153	0.283	
[3.4]	cum	0.095	0.240	0.692		0.032	0.035	0.362		-0.048	0.111	0.665	
[3.5]	cum	0.182	0.240	0.449		0.020	0.035	0.576		-0.072	0.111	0.516	
[3.6.1]	cum	0.310	0.247	0.209		0.019	0.038	0.608		0.066	0.114	0.565	
[3.6.2]	cum	0.112	0.240	0.640		0.026	0.038	0.495		-0.007	0.109	0.952	
[3.6.3]	cum	0.134	0.236	0.571		0.022	0.036	0.539		0.070	0.109	0.519	
[3.6.4]	cum	-0.488	0.241	0.043	*	0.052	0.037	0.153		-0.064	0.113	0.568	
[3.6.5]	cum	0.449	0.243	0.064		0.040	0.036	0.265		0.067	0.111	0.545	
[3.6.6]	cum	0.005	0.302	0.987		0.046	0.042	0.272		0.071	0.142	0.619	
[3.7.1]	cum	-0.355	0.245	0.148		-0.010	0.036	0.788		0.049	0.113	0.663	
[3.7.2]	cum	0.012	0.243	0.960		-0.011	0.035	0.744		0.103	0.112	0.358	
[3.7.3]	cum	-0.374	0.241	0.120		0.047	0.034	0.175		0.057	0.114	0.616	
[3.7.4]	cum	-0.135	0.244	0.581		-0.014	0.034	0.668		0.086	0.113	0.444	
[3.7.5]	cum	-0.647	0.250	0.009	**	-0.035	0.036	0.331		0.142	0.113	0.211	
[3.7.6]	cum	-0.670	0.248	0.007	**	-0.032	0.034	0.342		0.100	0.114	0.381	
[3.7.7]	cum	-0.100	0.244	0.683		0.018	0.037	0.634		-0.061	0.112	0.584	
[3.7.8]	cum	-0.484	0.243	0.047	*	-0.070	0.037	0.061		-0.041	0.113	0.716	
[3.8.1]	cum	0.099	0.249	0.690		0.047	0.037	0.207		-0.084	0.121	0.485	
[3.8.2]	cum	-0.129	0.243	0.595		0.040	0.035	0.250		0.171	0.115	0.136	
[3.8.3]	cum	-0.146	0.260	0.575		0.035	0.038	0.362		0.034	0.119	0.776	
[3.8.4]	cum	0.521	0.243	0.032	*	0.022	0.034	0.519		0.045	0.113	0.689	
[3.8.5]	cum	0.402	0.244	0.100		0.089	0.036	0.014	*	-0.001	0.114	0.992	
[3.8.6]	cum	0.593	0.250	0.018	*	0.095	0.036	0.008	**	0.082	0.117	0.484	
[3.9.1]	cum	0.634	0.247	0.010	*	-0.049	0.036	0.180		-0.021	0.112	0.852	
[3.9.2]	cum	-0.229	0.244	0.349		-0.042	0.033	0.213		-0.022	0.114	0.844	
[3.9.3]	cum	0.097	0.250	0.698		-0.043	0.038	0.263		0.009	0.115	0.935	
[3.9.4]	cum	0.047	0.243	0.848		0.000	0.036	0.997		-0.152	0.111	0.171	
[3.9.5]	cum	-0.015	0.246	0.952		-0.046	0.037	0.210		-0.156	0.114	0.173	
[3.9.6]	cum	-0.075	0.248	0.762		-0.082	0.035	0.018	*	-0.032	0.112	0.772	
[3.9.7]	cum	-1.273	0.284	0.000	***	0.029	0.043	0.505		-0.066	0.139	0.633	
[3.9.8]	cum	-0.888	0.297	0.003	***	0.037	0.045	0.412		0.034	0.149	0.820	
[3.9.9]	cum	-0.718	0.266	0.007	**	0.031	0.040	0.441		-0.146	0.128	0.255	
[3.10]	cum	-0.358	0.242	0.139		0.023	0.035	0.505		-0.126	0.112	0.260	
[3.11.1]	cum	-0.100	0.240	0.677		-0.013	0.036	0.726		-0.012	0.112	0.918	
[3.11.2]	cum	-0.136	0.239	0.569		-0.002	0.037	0.953		0.004	0.111	0.969	
[3.11.3]	cum	-0.235	0.246	0.339		0.064	0.037	0.086		0.017	0.113	0.880	
[3.11.4]	cum	-0.657	0.242	0.007	**	0.024	0.035	0.482		-0.028	0.111	0.798	
[3.11.5]	cum	0.143	0.250	0.566		0.037	0.037	0.315		0.043	0.118	0.718	
[3.11.6]	cum	-0.289	0.239	0.226		0.055	0.037	0.137		0.068	0.115	0.550	
[3.12]	cum	0.054	0.251	0.831		-0.008	0.033	0.813		-0.068	0.115	0.552	
[3.13]	log	-0.335	0.270	0.216		0.012	0.037	0.756		-0.119	0.127	0.351	
[3.14]	cum	0.034	0.247	0.889		0.017	0.037	0.655		-0.016	0.114	0.890	

Table 4. Results of a regression of gender (0 = male, 1 = female), age, and propensity to save on the answers in the "health insurance" part of the survey. For questions with two options, a logistic regression (log), for questions with more than two options, a cumulative logistic regression (cum) was performed.

7.3. FACTOR ANALYSIS

7.3.1. Motor insurance

The factor analysis is based on Questions 2.6, 2.7, 2.8.1 to 2.8.10, 2.9.1 to 2.9.6, 2.10.1 to 2.10.6, 2.11.1 to 2.11.7, 2.12, 2.13, 2.14. Principal factor solution with varimax rotation. 7 factors. The Tucker–Lewis index of factoring reliability is 1.097; the RMSEA index is 0.038.

Generally, only factor loadings with an absolute value of at least 0.4 are reported. Where lower factor loadings have been additionally considered for the interpretation, this is stated explicitly.

MPA1: Willingness to share driving data for insurance purposes	
[2.6] Would you share data with your insurance company for the calculation of a behavior-based insurance tariff?	0.48
[2.8] Which data about your driving style would you be willing to share with your insurer?	
[2.8.3] Time of car usage	0.45
[2.8.5] Speed driven	0.88
[2.8.6] Acceleration	0.85
[2.8.7] Braking	0.80
[2.8.8] Behavior in negotiating bends	0.78
[2.8.9] Distance to other vehicles	0.74
[2.11] Whom would you allow to collect data on your driving style?	
[2.11.5] Insurance companies	0.46

MPA2: Relaxed attitude with respect to privacy issues	
[2.8] Which data about your driving style would you be willing to share with your insurer?	
[2.8.2] Location (GPS-based)	0.44
[2.10] How severe are, from your perspective, the disadvantages for the customer that may result from an individualized motor insurance tariff?	
[2.10.1] Problems with data protection	−0.67
[2.10.3] Surveillance	−0.71
[2.11] Whom would you allow to collect data on your driving style?	
[2.11.4] Tech companies	0.73
[2.11.7] Telecommunication providers	0.49

MPA3: Willingness to share driving data in exchange for concrete benefits	
[2.8] Which data about your driving style would you be willing to share with your insurer?	
[2.8.1] Distance driven	0.67
[2.8.3] Time of car usage	0.67
[2.8.4] Using highways, rural or city roads	0.78
[2.9] How great are, from your perspective, the advantages for the customer that may result from an individualized motor insurance tariff?	
[2.9.3] Better evidence in case of damage	*0.32*
[2.9.4] Better assessment of fairness of premium	*0.36*
[2.9.5] Additional services (e.g., assistance in case of an accident)	0.45
[2.11] Whom would you allow to collect data on your driving style?	
[2.11.1] Car manufacturers	*0.38*

For MPA3, all loadings above 0.3 are reported.

MPA4: Concerns about a lack of solidarity and discrimination	
[2.10] How severe are, from your perspective, the disadvantages for the customer that may result from an individualized motor insurance tariff?	
[2.10.2] Higher premiums	0.42
[2.10.3] Surveillance	0.43
[2.10.4] Misplaced trust in technology	0.50
[2.10.5] Discrimination of bad drivers	0.71
[2.10.6] Reduced solidarity	0.65

MPA5: Desire for careful behavior to be rewarded	
[2.6] Would you share data with your insurance company for the calculation of a behavior-based insurance tariff?	0.49
[2.7] Should careful drivers benefit from a premium reduction?	0.74
[2.9] How great, from your perspective, are the advantages for the customer that may result from an individualized motor insurance tariff?	
[2.9.2] Premium reduction	0,56
[2.9.3] Better evidence in case of damage	0.59
[2.9.4] Better assessment of fairness of premium	0.43
[2.9.5] Additional services (e.g., assistance in case of accident)	0.45
[2.11] Whom would you allow to collect data on your driving style?	
[2.11.3] Emergency services (police, ambulance, etc.)	0.43
[2.12] To what extent would you feel uncomfortable with your driving being tracked?	−0.40
[2.13] Should careless drivers pay higher motor insurance premiums?	0.57
[2.14] To what extent would you, in your opinion, benefit from a behavior-based insurance tariff?	0,46

MPA6: General willingness to share driving data	
[2.11] Whom would you allow to collect data on your driving style?	
[2.11.1] Car manufacturers	0.63
[2.11.2] Government	0.61
[2.11.5] Insurance companies	0.42
[2.11.6] Energy suppliers	0.62
[2.11.7] Telecommunication providers	0.61
[2.12] To what extent would you feel uncomfortable with your driving being tracked?	−0.50

MPA7: Driving data as evidence in case of an accident	
[2.8] Which data about your driving style would you be willing to share with your insurer?	
[2.8.10] Driving behavior 20 seconds before and 10 seconds after accident)	0.71

7.3.2. Health insurance

The factor analysis is based on Questions 3.4, 3.5, 3.6.1 to 3.6.6, 3.7.1 to 3.7.8, 3.8.1 to 3.8.6, 3.9.1 to 3.9.9, 3.10, 3.11.1 to 3.11.6. Principal factor solution with varimax rotation. 9 factors. The Tucker–Lewis index of factoring reliability is 0.738; the RMSEA index is 0.1.

Generally, only factor loadings with an absolute value of at least 0.4 are reported. Where lower factor loadings have been additionally considered for the interpretation, this is stated explicitly.

HPA1: Willingness to share health data for insurance purposes	
[3.5] Would you be prepared to provide data on your health-related behavior to benefit from a premium reduction for your basic health insurance?	0.67
[3.6] What data would you be willing to share with your insurer in exchange for a premium reduction?	
[3.6.1] Steps walked	0.71
[3.6.2] Routes walked	0.70
[3.6.3] Data of a pulse monitor	0.79
[3.6.4] Calorie intake	0.69
[3.6.5] Amount of sleep	0.71
[3.6.6] Location	0.52
[3.7] How great, from your perspective, would be the advantages of an individualized health insurance tariff?	
[3.7.3] Comparison with others	0.42
[3.9] Whom would you allow to collect data on your health-related behavior?	
[3.9.4] Health insurance companies	0.42

HPA2: Desire for careful behavior to be rewarded	
[3.10] Should unhealthy behavior result in a higher premium for basic health insurance?	0.56
[3.11] What type of behavior should lead to a higher premium for basic health insurance?	
[3.11.1] Smoking	0.59
[3.11.2] Alcohol consumption	0.73
[3.11.3] Workaholism	0.69
[3.11.4] Risky sport activities	0.44
[3.11.5] Meat consumption	0.78
[3.11.6] Sugar consumption	0.79

HPA3: Willingness to share health data outside the healthcare industry	
[3.6] What data would you be willing to share with your insurer in exchange for a premium reduction?	
[3.6.6] Location	0.43
[3.9] Whom would you allow to collect data on your health-related behavior?	
[3.9.5] Other insurance companies	0.45
[3.9.7] Tech companies	0.88
[3.9.8] Telecommunication providers	0.86
[3.9.9] Large retailers	0.74

HPA4: Belief that individualized health insurance tariffs are useful	
[3.7] How great, from your perspective, would be the advantages of an individualized health insurance tariff?	
[3.7.4] Reminders about medication schedule	0.55
[3.7.5] Help with chronic illness	0.78
[3.7.6] Emergency assistance	0.72
[3.7.8] Reduction of my healthcare costs	0.51

HPA5: Belief that disadvantages are small	
[3.8] How great, from your perspective, are the disadvantages of an individualized health insurance tariff for the customer?	
[3.8.1] Problems with data protection	−0.42
[3.8.2] Higher premiums	−0.41
[3.8.3] Surveillance	−0.52
[3.8.4] Misplaced trust in technology	−0.59
[3.8.5] Discrimination of people suffering from chronic illnesses	−0.81
[3.8.6] Reduced solidarity	−0.76

HPA6: Willingness to share health data with health-related organizations	
[3.9] Whom would you allow to collect data on your health-related behavior?	
[3.9.1] Government	0.68
[3.9.2] Hospitals	0.76
[3.9.3] Pharmaceutical companies	0.43
[3.9.4] Health insurance companies	0.52
[3.9.5] Other insurance companies	0.40
[3.9.6] Emergency services	0.64

HPA7: Belief that individualized tariffs can be use-ful in promoting a healthier lifestyle	
[3.7] How great, from your perspective, would be the advantages of an individualized health insurance tariff?	
[3.7.1] Personalized health advice	0.75
[3.7.2] Personalized training schedule	0.68

HPA8: Belief that health data can reduce insur-ance premiums and healthcare spending	
[3.4] Should people be granted a premium reduction for their compulsory health insurance if they can prove, by means of a mobile health-app or a fitness tracker, that they have a healthy lifestyle?	0.53
[3.5] Would you be prepared to provide data on your health-related behavior to benefit from a premium reduction for your basic health insurance?	0.44
[3.7] How great, from your perspective, would be the advantages of an individualized health insurance tariff?	
[3.7.7] Rebate for health insurance premium	0.53
[3.7.8] Reduction of my healthcare costs	0.48
[3.8] How great, from your perspective, are the disadvantages of an individualized health insurance tariff for the customer?	
[3.8.2] Higher premiums	−0.41

HPA9: Unwillingness to collectivize avoidable risks	
[3.8] How great, from your perspective, are the disadvantages of an individualized health insurance tariff for the customer?	
[3.8.1] Problems with data protection	*0.35*
[3.10] Should unhealthy behavior result in a higher premium for basic health insurance?	*0.33*
[3.11] What type of behavior should lead to a higher premium for basic health insurance?	
[3.11.1] Smoking	0.55
[3.11.2] Alcohol consumption	*0.31*

For PA9, all loadings above 0.3 are reported.

7.3.3. Regressions

		Gender				Age				Propensity to save			
		β	s	p		β	s	p		β	s	p	
MPA1	lin	0.512	0.242	0.038	*	0.041	0.030	0.175		-0.074	0.112	0.509	
MPA2	lin	-0.251	0.250	0.320		0.012	0.031	0.706		0.181	0.115	0.122	
MPA3	lin	0.026	0.248	0.916		0.014	0.031	0.650		-0.217	0.114	0.063	
MPA4	lin	0.025	0.254	0.921		0.014	0.032	0.650		0.193	0.117	0.104	
MPA5	lin	-0.171	0.259	0.510		-0.012	0.032	0.701		0.008	0.119	0.944	
MPA6	lin	-0.162	0.250	0.519		0.022	0.031	0.478		-0.250	0.115	0.033	*
MPA7	lin	-0.123	0.258	0.634		0.013	0.032	0.681		0.030	0.119	0.804	
HPA1	lin	0.247	0.131	0.061		0.026	0.018	0.159		0.015	0.062	0.803	
HPA2	lin	-0.005	0.134	0.972		0.028	0.019	0.143		0.000	0.063	0.995	
HPA3	lin	-0.649	0.127	0.000	***	0.033	0.018	0.061		-0.043	0.060	0.469	
HPA4	lin	-0.415	0.131	0.002	***	-0.026	0.018	0.163		0.056	0.061	0.362	
HPA5	lin	-0.257	0.131	0.050		-0.043	0.018	0.018	*	-0.006	0.062	0.918	
HPA6	lin	0.288	0.131	0.029	*	-0.037	0.018	0.043	*	-0.033	0.062	0.588	
HPA7	lin	-0.017	0.133	0.897		-0.008	0.019	0.684		0.053	0.062	0.396	
HPA8	lin	-0.051	0.132	0.698		0.011	0.018	0.536		-0.079	0.062	0.205	
HPA9	lin	-0.367	0.130	0.005	**	-0.031	0.018	0.091		-0.036	0.061	0.561	

Table 5. Results of a linear regression (lin) of gender (0 = male. 1 = female), age, and propensity to save on the factor scores.

	β	s	p	
[2.5]	-1.287	0.976	0.187	
[2.14]	2.185	0.758	0.004	***
MPA1	-0.638	0.511	0.212	
MPA2	0.482	0.415	0.245	
MPA3	0.703	0.463	0.129	
MPA4	-1.466	0.608	0.016	*
MPA5	0.883	0.465	0.057	
MPA6	0.966	0.466	0.038	*
MPA7	0.581	0.411	0.157	

	β	s	p	
[3.3]	0.029	0.380	0.939	
[3.12]	0.581	0.209	0.005	**
HPA1	0.768	0.175	0.000	***
HPA2	0.729	0.184	0.000	***
HPA3	0.331	0.185	0.073	
HPA4	0.444	0.182	0.014	*
HPA5	0.413	0.176	0.019	*
HPA6	0.660	0.186	0.000	***
HPA7	0.624	0.179	0.000	***
HPA8	1.110	0.196	0.000	***
HPA9	0.111	0.164	0.498	

Table 6. Results of a logistic regression of the preference for an individualized tariff (left table: motor insurance, [2.15]; right table: health insurance, [3.13]).

8. Figures

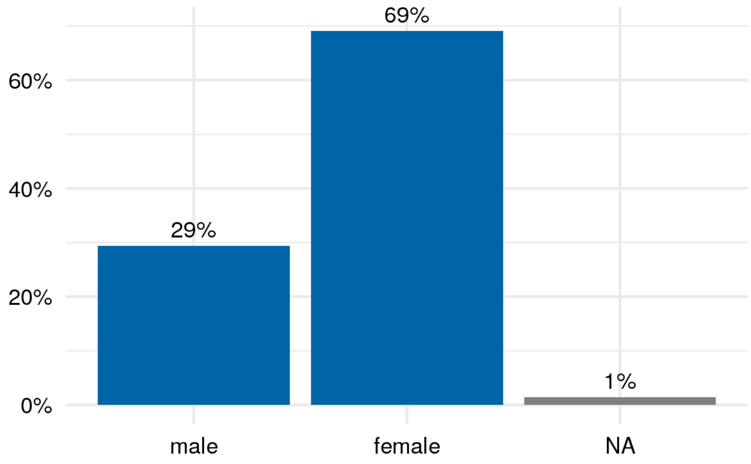

Figure 1. [1.1] Gender (NA = no answer).

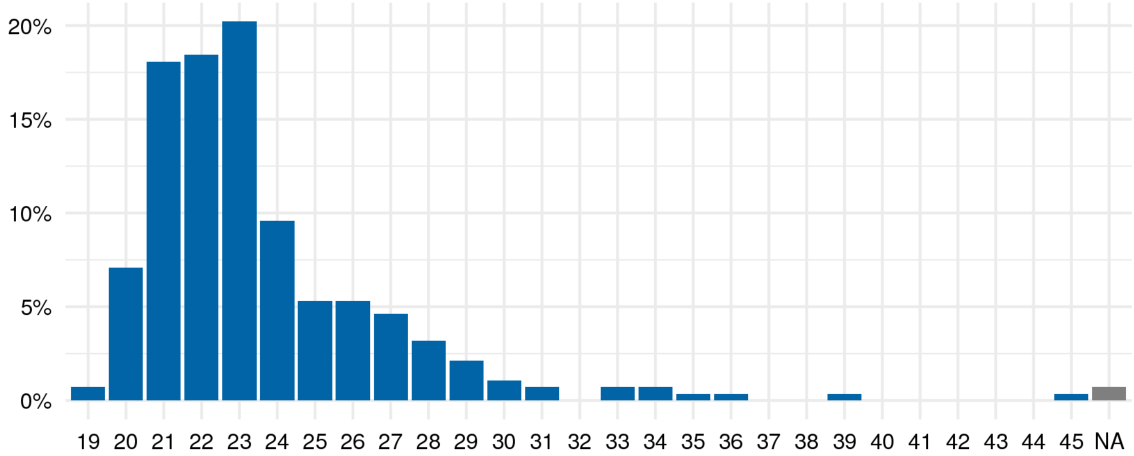

Figure 2. [1.2] Age (NA = no answer).

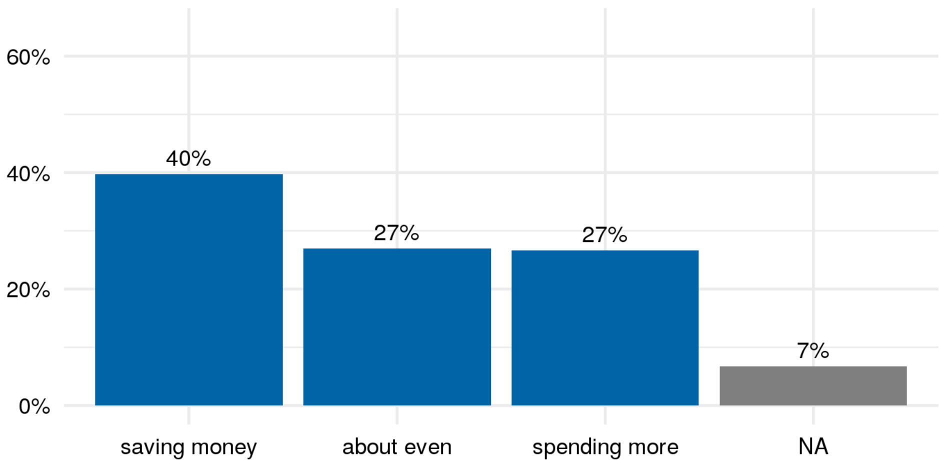

Figure 3. [1.3] What is the relationship between income and spending in your household? (NA = no answer or "do not know").

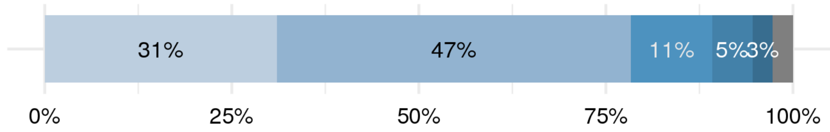

Figure 4. [2.2] Do you consider yourself to be a careful driver? (Five-step scale from "yes" [light blue] to "no" [dark blue], NA = no answer).

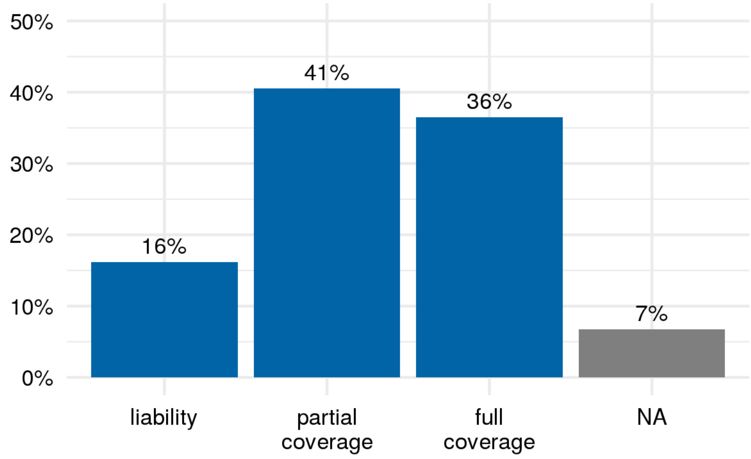

Figure 5. [2.3] What insurance coverage do you currently have? (NA = no answer or "do not know").

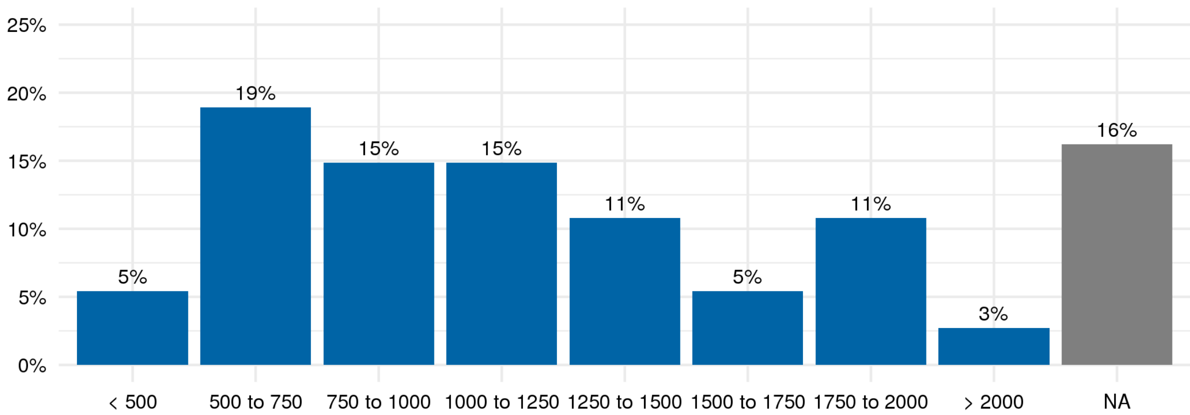

Figure 6. [2.4] What is your annual premium for motor insurance? (in CHF; NA = no answer or "do not know").

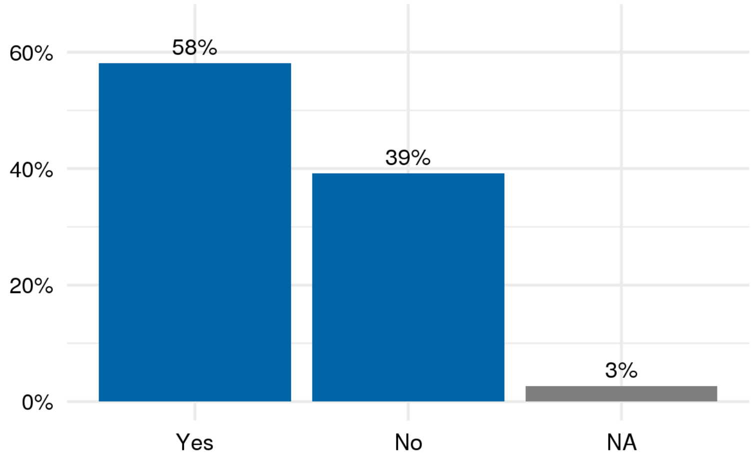

Figure 7. [2.5] Have you heard of individualized or behavior-based motor insurance (based on trip recorders or GPS trackers)? (NA = no answer).

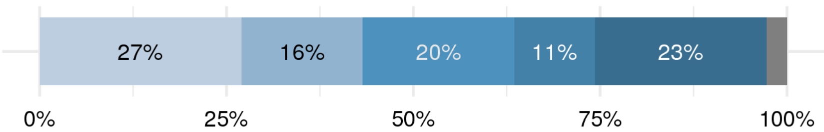

Figure 8. [2.6] Would you share data with your insurance company for the calculation of a behavior-based insurance tariff? (Five-step scale from "yes" [light blue] to "no" [dark blue], NA = no answer).

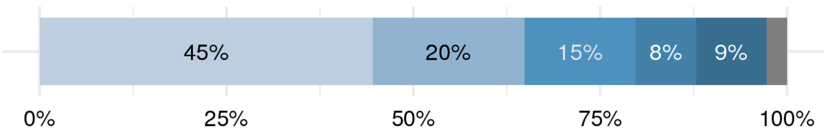

Figure 9. [2.7] Should careful drivers benefit from a premium reduction? (Five-step scale from "yes" [light blue] to "no" [dark blue], NA = no answer).

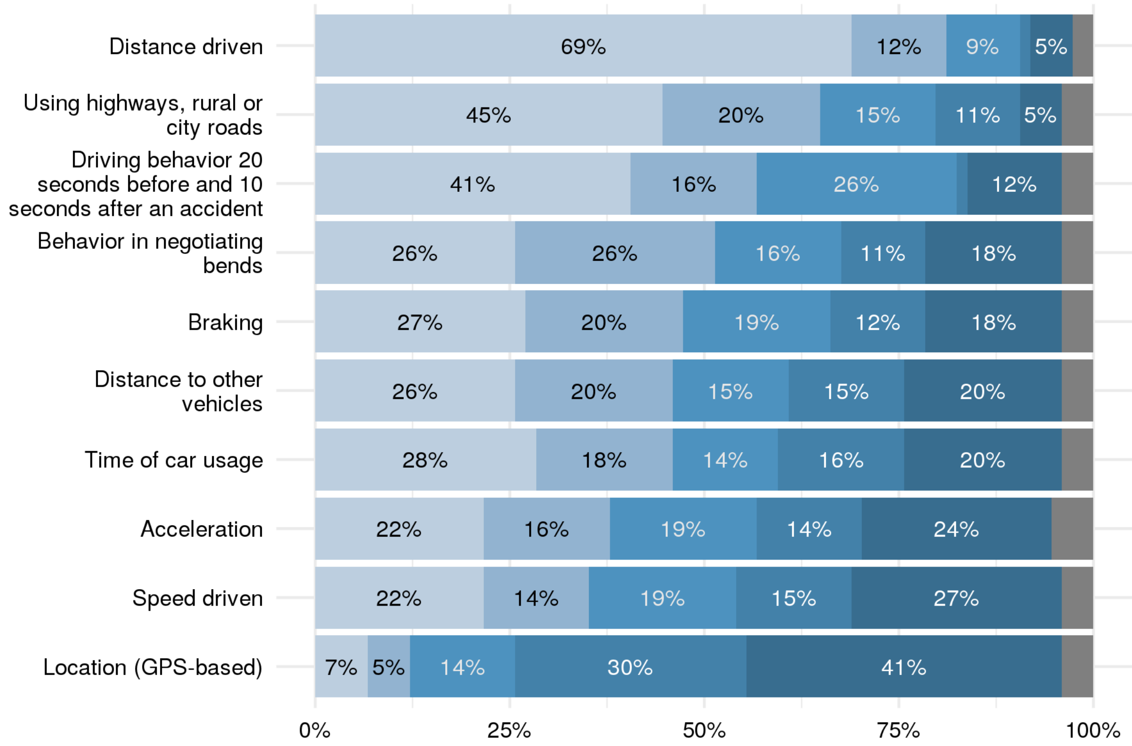

Figure 10. [2.8] Which data about your driving style would you be willing to share with your insurer? (Five-step scale from "yes" [light blue] to "no" [dark blue], grey: no answer).

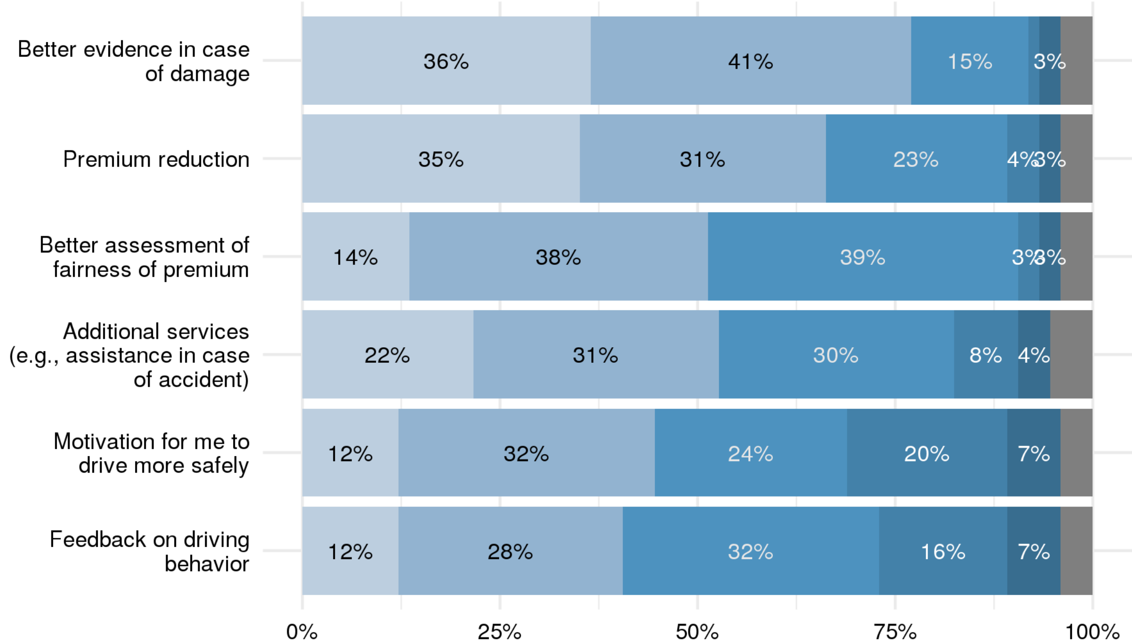

Figure 11. [2.9] How great, from your perspective, are the advantages for the customer that may result from an individualized motor insurance tariff? (Five-step scale from "very high" [light blue] to "very low" [dark blue], grey: no answer).

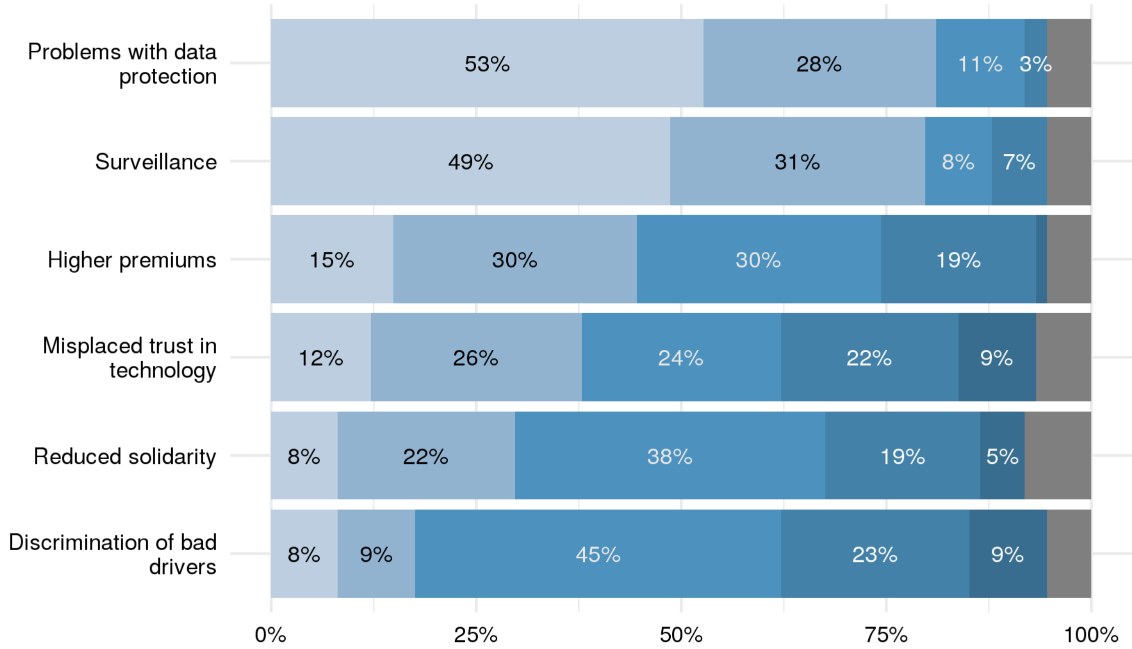

Figure 12. [2.10] How severe are, from your perspective, the disadvantages for the customer that may result from an individualized motor insurance tariff? (Five-step scale from "very high" [light blue] to "very low" [dark blue], grey: no answer).

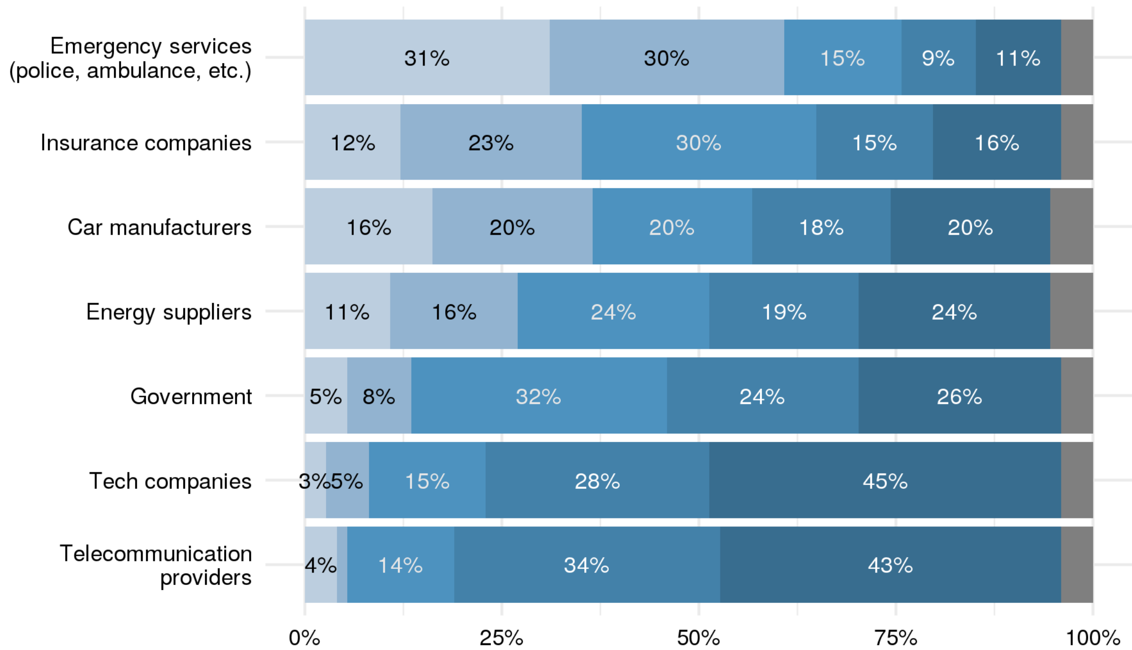

Figure 13. [2.11] Whom would you allow to collect data on your driving style? (Five-step scale from "yes" [light blue] to "no" [dark blue], grey: no answer).

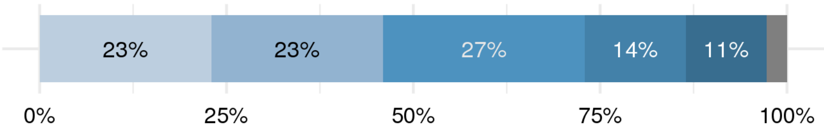

Figure 14. [2.12] To what extent would you feel uncomfortable with your driving being tracked? (Five-step scale from "very uncomfortable" [light blue] to "not uncomfortable at all" [dark blue], grey: no answer).

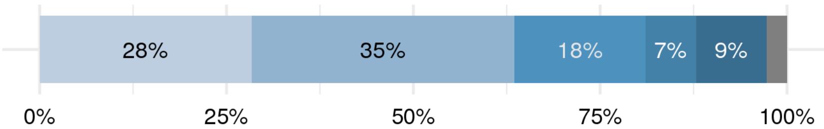

Figure 15. [2.13] Should careless drivers pay higher motor insurance premiums? (Five-step scale from "yes" [light blue] to "no" [dark blue], grey: no answer).

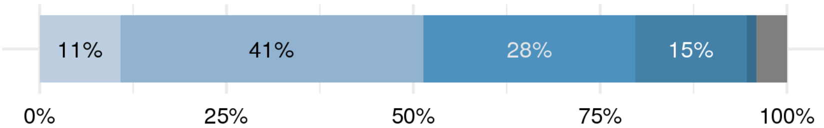

Figure 16. [2.14] To what extent would you, in your opinion, benefit from a behavior-based insurance tariff? (Five-step scale from "extremely" [light blue] to "not at all" [dark blue], grey: no answer).

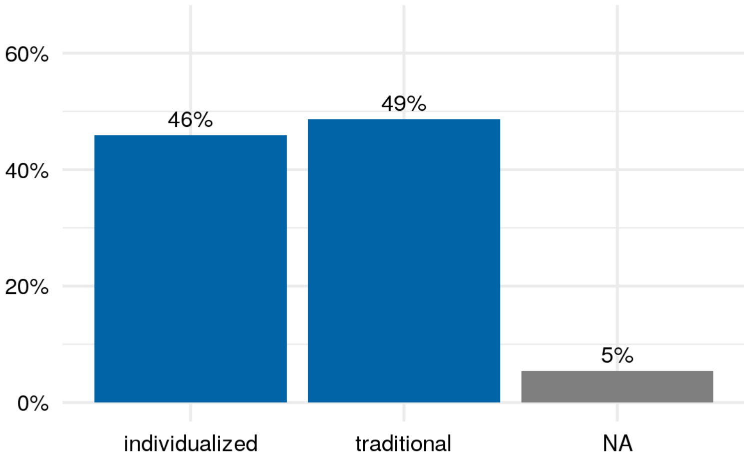

Figure 17. [2.15] Would you prefer individualized over traditional insurance? (NA = no answer).

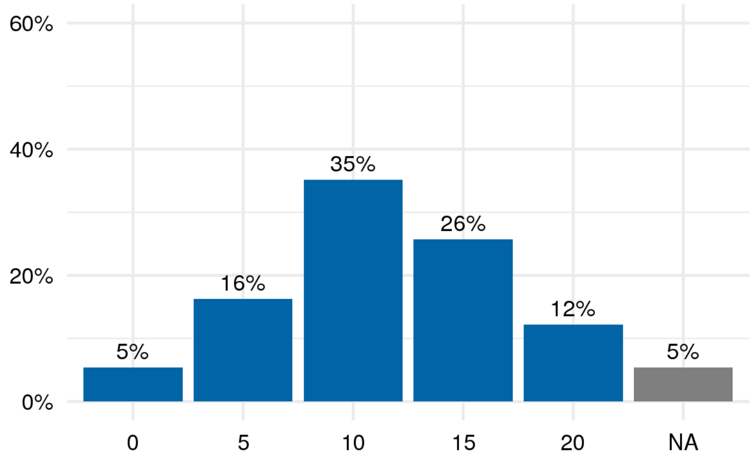

Figure 18. [2.16] Given your driving style, what premium reduction in motor insurance would you expect to receive? (in percent, NA = no answer).

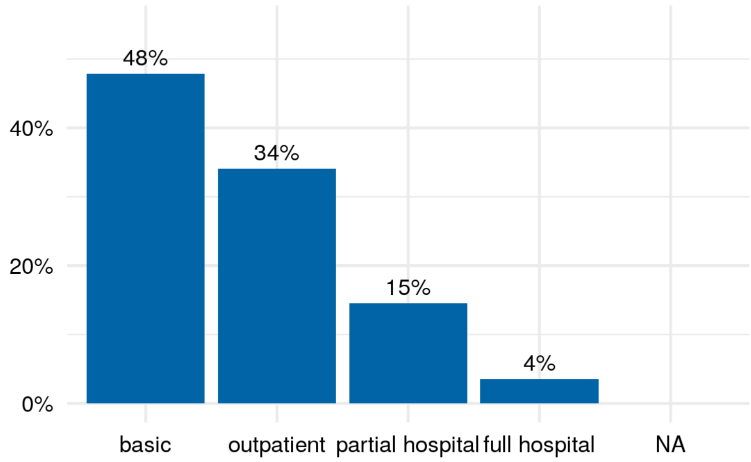

Figure 19. [3.1] What type of health insurance do you currently have? (mandatory basic health insurance/supplementary outpatient insurance/partial supplementary hospital insurance/full supplementary hospital insurance, NA = no answer).

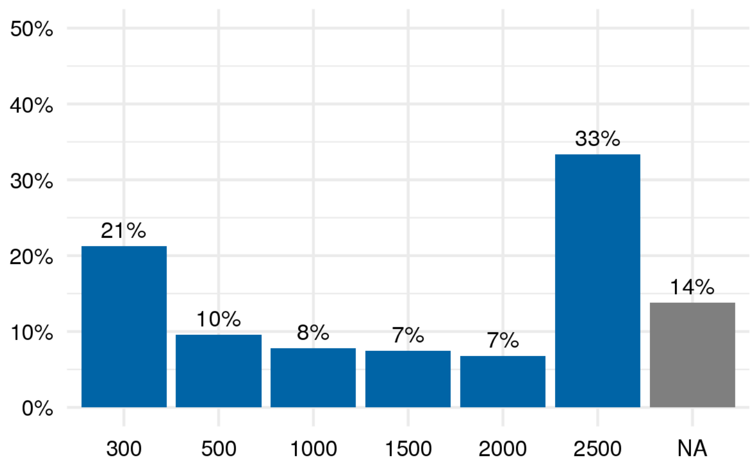

Figure 20. [3.2] What is currently your deductible for your basic health insurance? (in CHF, NA = no answer).

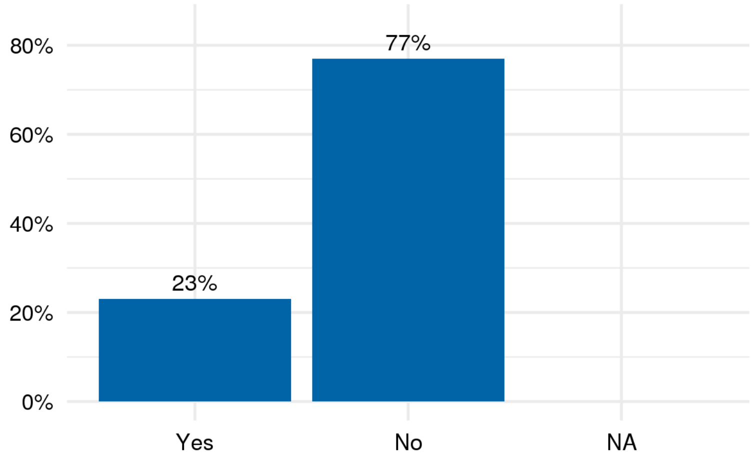

Figure 21. [3.3] Do you use a mobile health app (step counter, pulse monitor, etc.) or a fitness tracker/smart watch? (NA = no answer).

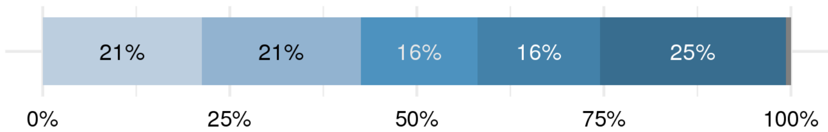

Figure 22. [3.4] Should people be granted a premium reduction for their compulsory health insurance if they can prove, by means of a mobile health-app or a fitness tracker, that they have a healthy lifestyle? (Five-step scale from "yes" [light blue] to "no" [dark blue]. NA = no answer).

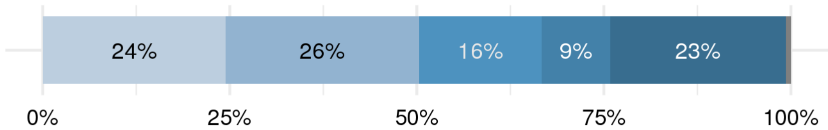

Figure 23. [3.5] Would you be prepared to provide data on your health-related behavior to benefit from a premium reduction for your basic health insurance? (Five-step scale from "yes" [light blue] to "no" [dark blue]. NA = no answer).

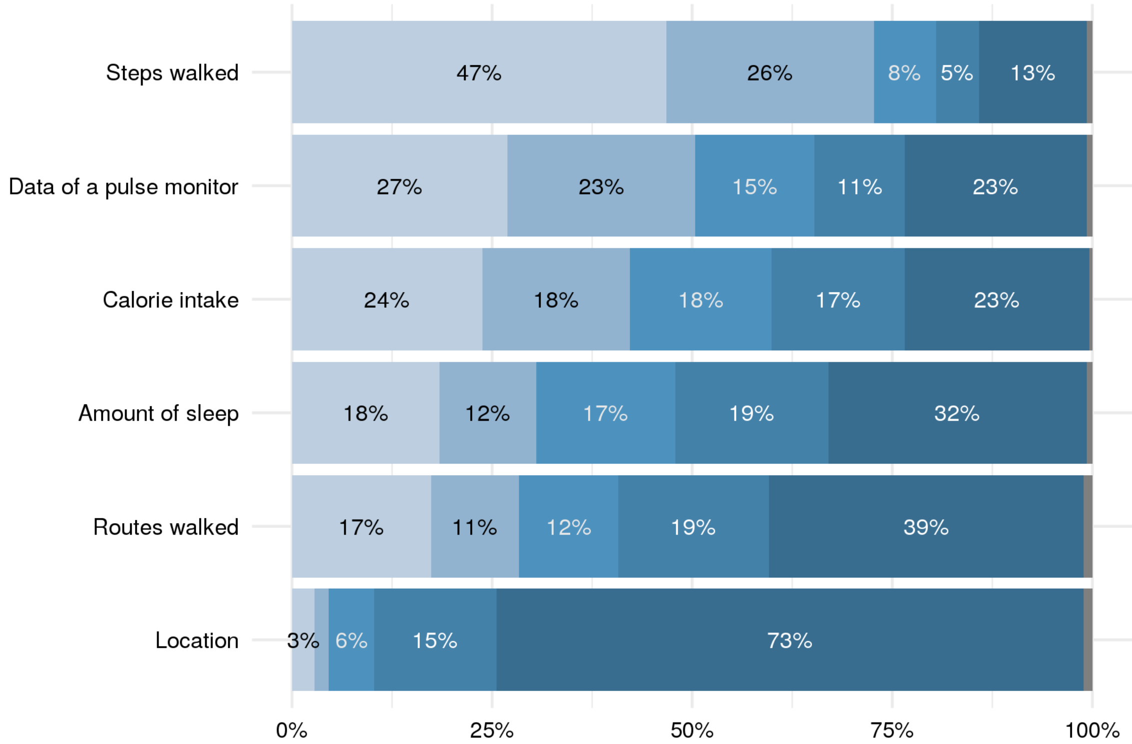

Figure 24. [3.6] What data would you be willing to share with your insurer in exchange for a premium reduction? (Five-step scale from "yes" [light blue] to "no" [dark blue]; grey: no answer).

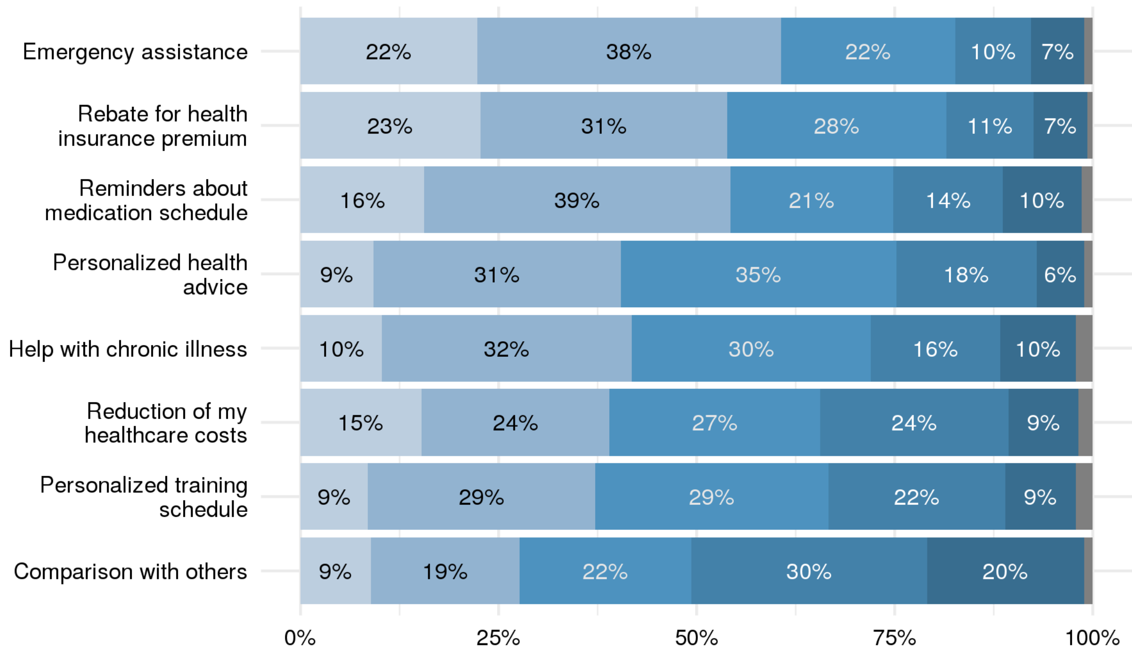

Figure 25. [3.7] How great, from your perspective, would be the advantages of an individualized health insurance tariff? (Five-step scale from "very high" [light blue] to "very low" [dark blue] grey: no answer).

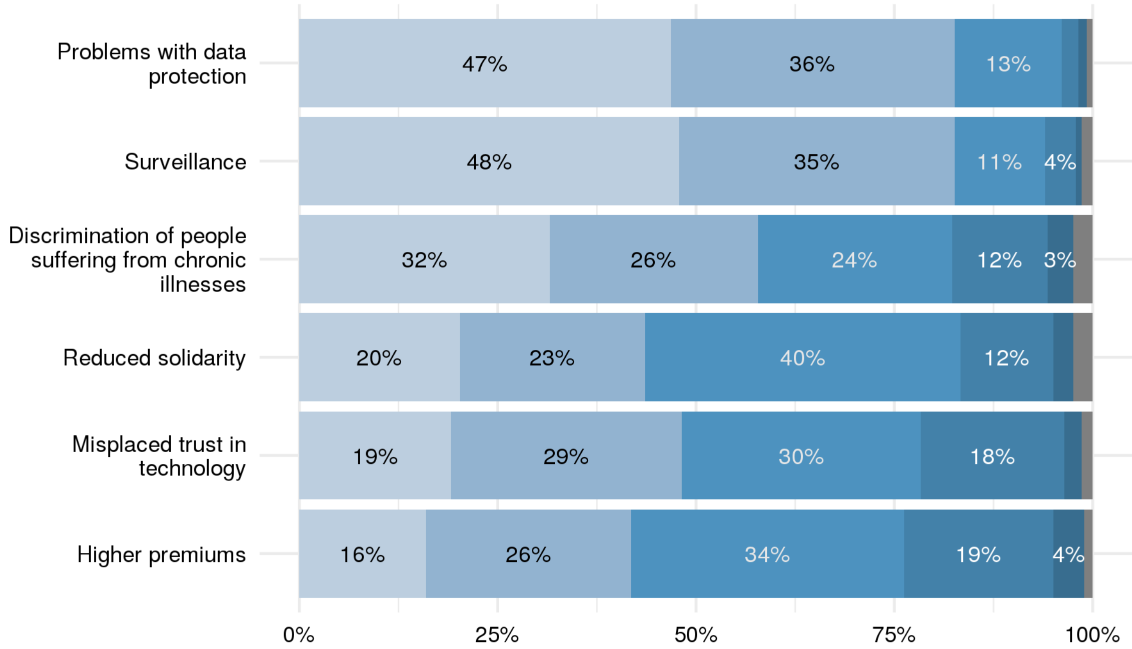

Figure 26. [3.8] How great, from your perspective, are the disadvantages of an individualized health insurance tariff for the customer? (Five-step scale from "very high" [light blue] to "very low" [dark blue], grey: no answer).

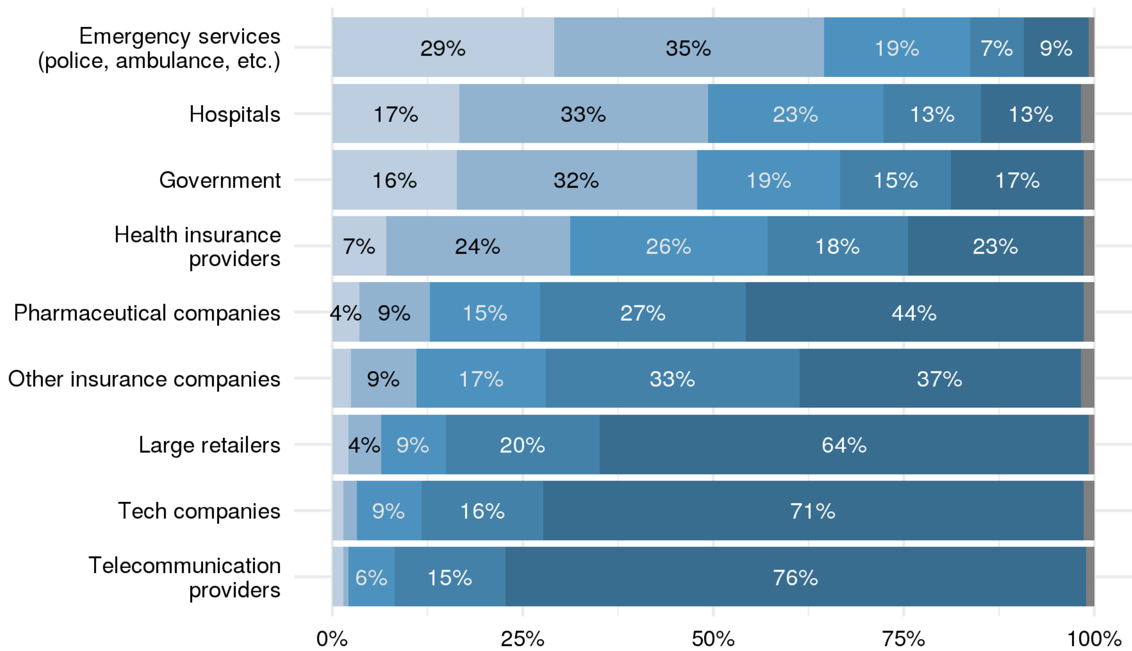

Figure 27. [3.9] Whom would you allow to collect data on your health-related behavior? (Five-step scale from "yes" [light blue] to "no" [dark blue], grey: no answer).

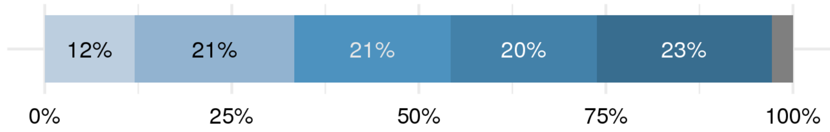

Figure 28. [3.10] Should unhealthy behavior result in a higher premium for basic health insurance? (Five-step scale from “yes” [light blue] to “no” [dark blue], NA = no answer).

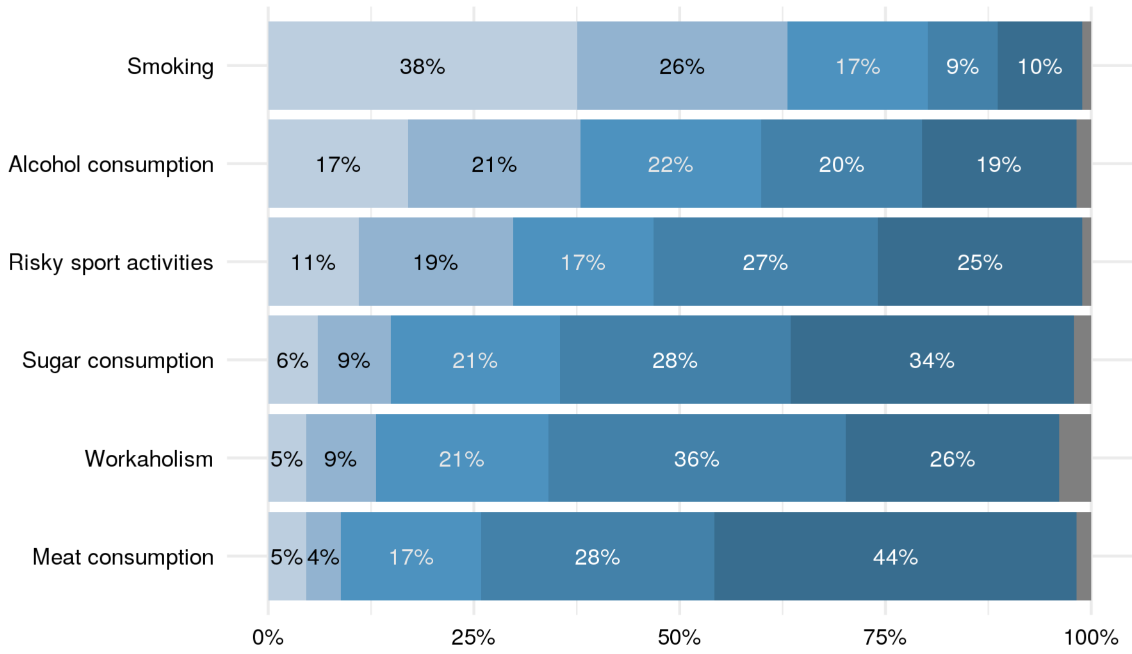

Figure 29. [3.11] What type of behavior should lead to a higher premium for basic health insurance? (Five-step scale from “yes” [light blue] to “no” [dark blue], grey: no answer).

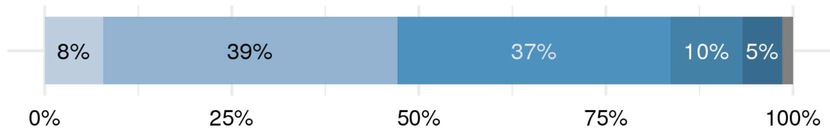

Figure 30. [3.12] To what extent would you, in your opinion, benefit from a behavior-based tariff? (Five-step scale from “extremely” [light blue] to “not at all” [dark blue], grey: no answer).

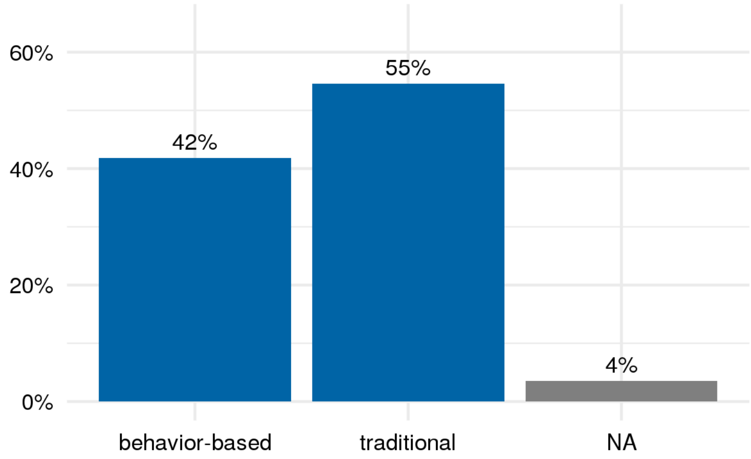

Figure 31. [3.13] Would you prefer a behavior-based or a traditional health insurance tariff? (NA = no answer).

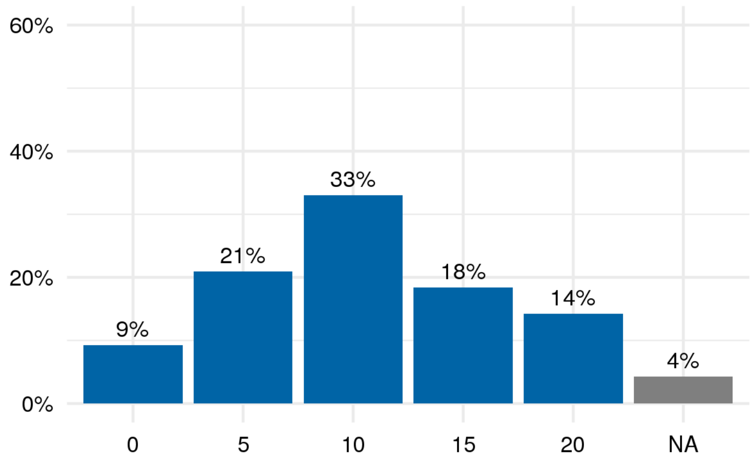

Figure 32. [3.14] Given your lifestyle, what premium reduction for your health insurance would you expect to receive? (in percent, NA = no answer).

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