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Financial Incentives and Intention to Subscribe to Data-Driven Health Plans

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Completed Research Paper

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Abstract

Over the last years, health insurance companies have displayed considerable dynamism in integrating quantified-self-devices (such as smartwatches and activity trackers) in their business models to create data-driven health plans built around these systems. In order to motivate consumers to participate in these programs — and share their data — health insurance companies often make use of financial incentives. Yet, there is little evidence on the effects of discounts or rewards on individual intention to subscribe to data-driven health plans. In particular, little is known about the type of consumers for which financial incentives serve as a trigger for participation. In this paper, we thus report results from a survey made in Switzerland, which constitues a representative context of consumers' choice in a liberal health insurance market, about consumers' intention to participate in (incentivized) data-driven health plans. By doing so, we seek to lay the foundations for a better comprehension of individuals' aspirations and drivers to engage into these programs.

Keywords: Quantified self devices, financial incentives, health insurance companies, data-driven health plans

Introduction

The way the wider masses perceive their health levels has evolved since the 2000's: information based on data and numbers have penetrated the collective awareness and many have become reliant on data analytics and algorithms to find out whether they have done enough physical activity; they have slept well or their diet is appropriate (Ajana 2017; Lupton 2016). This was made possible by the rapid development and the large commercialization of wearable systems that track individual behaviors, physical capacities, psychological wellness or environment parameters, in order to offer a quantified feedback to improve individual condition and performance (Wilson 2013). This new paradigm of individual empowerment and self-management through health data (commonly referred to as the *quantified self* movement) has also spread across the healthcare sector (Lupton 2016; Ruckenstein and Pantzar 2017; Swan 2013). We find today quantified self devices as cornerstones of many programs for physical therapy, patient monitoring, chronic disease management and preventive care (Appelboom et al. 2014; Marakhimov and Joo 2017). In particular, one key healthcare actor is showing a high interest in quantified self devices: health insurance companies. According to an industry report made in 2015 across 221 insurance companies in the world, 31% of the respondents have adopted this technology in one of their programs, while 61% were considering to incorporate quantified self practices in a foreseeable future (Accenture 2015). In fact, accessing to a constant tracking of physical or behavioral levels may allow health insurance companies to meet most of their commercial and organizational objectives, such as supervising the evolution of chronic conditions among the population, strengthening the range of provided health services, offering new insurance products and fostering consumers' engagement (Henkel et al. 2018; Lewalle 2006; Samuel and Connolly 2015; Tedesco et al. 2017). Yet, such health data tracking may also allow to identify potential health risk behaviors among users (which could impact how health insurance companies determine premiums) or characterize individual behaviors for further marketing and commercialization considerations (Constantiou and Kallinikos 2015; Tedesco et al. 2017).

In order to motivate data sharing from consumers, health insurance companies often resort to financial incentives, as motivational mechanisms to increase adoption rates and reduce resistance (Henkel et al. 2018; Paluch and Tuzovic 2019). Discounts or rewards are offered to consumers that link a quantified self device to company's dedicated app and, then, attain some objectives or challenges (e.g. averaging 7,000 steps per day). However, little is known about the effects of financial incentives on individual intention to subscribe to data-driven health plans and, specifically, if financial incentives act as a trigger for some types of consumers to engage in such programs. In fact, as academic attention directed towards data-driven health plans have started to grow, the main foci were either (1) privacy challenges (e.g. Patterson 2013); (2) individual willingness to disclose health data (e.g. Von Entreß-Fürsteneck et al. 2019) or (3) concrete applications of quantified self devices in these plans (e.g. Henkel et al. 2018; Tedesco et al. 2017). Thus, despite an emerging interest, there is little evidence on the effects of financial incentives, which may be determining in consumers' choice to subscribe to data-driven health plans. Such knowledge is not only essential to better understand individuals' aspirations and drivers to engage into these programs, but may also help health insurance companies, technology providers, and healthcare professionals to get insights about health-related behaviors of consumers who are willing to share health data, in order to ensure a successful integration of quantified self devices in their respective programs (Paré et al. 2018). This is particularly essential in the context of a market-oriented health insurance system, as the viability of a complimentary plan depends on the understanding of consumers' demands, preferences and level of access (Uschold et al. 2005).

Accordingly, we set out the following research question: *What are the effects of financial incentives in the intention to subscribe to data-driven health plans?*

To adequately explore this issue, our investigation has to be carried in a liberal healthcare system, where residents have choice options. This is the case of Switzerland, as permanent residents have to enroll in a basic insurance plan (individual free choice among state recognized private insurance providers) that supports elementary healthcare needs (i.e. covers the costs of the examination and treatment of a medical condition and its consequences). Additionally, permanent residents can contract any type of supplementary coverage (such as data-driven health plans), which is a standard practice in Switzerland, as more than 70% of permanent residents subscribe to some extra plans (Laske-Aldershof et al. 2004; Schoen et al. 2010). In all cases, the Swiss health insurance system shares numerous similarities (as regards health needs, economic opportunities and political context) with other healthcare systems across Europe (e.g. Germany, the Netherlands) and North America (Schoen et al. 2010; Thomson et al. 2014). This is why we believe that our paper provides evidence and reflection that can be generalizable for a multitude of contexts. We thus present findings which are based on a survey conducted with a representative sample of Swiss permanent residents regarding their intention to participate in data-driven health plans.

The remainder of this paper is structured as follows: we first introduce the notion of quantified self and then detail their connection to data-driven health plans. With reference to the literature, we next investigate the main dynamics and factors in the individual rationale of subscribing to data-driven health plans and accordingly develop our survey. We then test the effects of financial incentives and their interaction with other key factors, using a sample of 441 people, who were randomly selected to participate in our study. We conclude by discussing the results, the limitations of our analysis as well as the opportunities for future research.

Background

In the quantified self movement, there is a deep conviction that self-knowledge can be enhanced through numbers by regularly gathering data on oneself to better apprehend routines, behaviors and feelings (Choe et al. 2014; Lupton 2014b; Swan 2012b). The body is seen and framed as something that can be measured and quantified. The corresponding data is then automatically analyzed, plotted and even evaluated, so that individuals are provided with information that may guide them in a course of action (Heyen 2016; Whitson 2013). There is therefore a proactive stance that individuals themselves may be the focus and the center of action taking (Swan 2012a), as they are in position to collect health information and act based on it (Li et al. 2011; Whooley et al. 2014). For this reason, the notion of transparency is a key element of the quantified self movement: *self-quantifiers* are eager to unveil performance and "make existence knowable" (Didžiokaitė et al. 2018; Ruckenstein and Pantzar 2017). This ensures an optimization of their health levels by unlocking realizable, although initially vague, opportunities (Meißner 2016; Ruckenstein and Pantzar 2017). Eventually, communication also constitutes a fundamental pillar of the quantified self movement, because individuals acquire benchmarks (due to standardized measurements and visualizations) that allow them to share, compare and discuss health data. This can be done according to user's own data history but also compared to others, which explains why quantified self devices are often accompanied by web platforms or applications that enable resource-sharing (Heyen 2016; Meißner 2016).

In practice, quantified self-devices are wearable self-reliant systems that allow the monitoring of a wide range of vital parameters (e.g. blood pulse rate, oxygen saturation, body temperature), physical and behavioral activity (body movement calories used), mental status (e.g. mood, attention, stress), and environmental variables (e.g. noise, pollution, distance covered). They aim to better apprehend individuals' behaviors, enhance wellness and act on health levels (Choe and Fesenmaier 2017; Glaros and Fotiadis 2005; Gorm 2017; Lavallière et al. 2016). Considerable amounts of quantified self devices have been developed in the past years for the consumer market, going from activity trackers to complex systems derived from medical contexts (Mettler and Wulf 2020). Such diversity is due to the involvement of a large panel of new actors (West et al. 2016) that are coming from various sectors, such as the sport industry (e.g. *Under Armour, Nike*), consumer IT (e.g. *Garmin, Apple, Samsung*) or fashion (e.g. *Fossil*). With their active presence in the consumer market, these kinds of companies have constantly improved quantified self devices in terms of affordability, miniaturization, capacity to store data, and accuracy of health sensors (Heyen 2016; Lavallière et al. 2016; Stepanovic et al. 2019) making them accessible to a large number of people.

As a consequence of the wide dissemination of low-pricing quantified self devices such as activity trackers or smart wristbands in the consumer market, prior research has primarily concentrated on the study of quantified self devices for private use (Mettler and Wulf 2020). In fact, the research effort has been rather prolific (De Moya and Pallud 2017). The most recurring themes and discussions have covered adoption factors (e.g. Canhoto and Arp 2017; Li et al. 2016), privacy challenges (e.g. Mills et al. 2016; Piwek et al. 2016), use experiences (e.g. Kim 2014; Shin and Biocca 2017), self-experimentation (Karkar et al. 2015), styles of tracking (Rooksby et al. 2014), post-adoptive use (e.g. Buchwald et al. 2015; Marakhimov and Joo 2017), design (e.g. Epstein et al. 2015; Rapp and Cena 2014), and quantified self as a cultural and societal phenomenon (Choe et al. 2014; Lupton 2014c; Ruckenstein and Pantzar 2017; Swan 2013). In contrast, the attention on quantified self devices provided by third parties is starting to grow, as more and more investments are made by government agencies and businesses in order to harness health-related information obtained from quantified self devices (Lupton 2014a; Paluch and Tuzovic 2019). As outlined, health insurance companies are particularly active in this regard, because quantified self devices are seen as new opportunities to gain control on health expenditure and improve health service delivery (Mettler and Wulf 2020; Patterson 2013; Tedesco et al. 2017). As opposed to passive forms of information provision, the information collected by sensors may provide with more accurate and contextualized health advice (King et al. 2015; Mettler and Wulf 2020). Such companies are therefore attracted by the promises of accuracy, precision and efficiency in collecting information that quantified self devices offer (Dargazany et al. 2018). This may generate favorable conditions to reduce health costs, create new insurance products and services, or enhance engagement of consumers (Henkel et al. 2018; Samuel and Connolly 2015; Tedesco et al. 2017). For academics, privacy challenges and individual adoption remain the main focal points. In particular, scholars have acknowledged that potential security breaches, disruption of private life, fear of a discrimination based on health levels and unwanted targeted marketing have been the key individual concerns regarding the use of quantified self devices in a data-driven health plan (Cheung et al. 2016; Paluch and Tuzovic 2019; Patterson 2013; Von Entreß-Fürsteneck et al. 2019). Likewise, perceived data sensitivity has been found to exercise a moderating effect on this risk-benefits analysis, with a willingness to share data being more predominant for data such as steps or distance walked, and less for information such as heart rate or rhythm, blood pressure or weight (Von Entreß-Fürsteneck et al. 2019). In any case, evidence shows that data-driven health plans are starting to be proposed by health insurance companies across most industrialized countries (Dargazany et al. 2018). This is particularly perceivable in settings where the employer constitutes the link between quantified self devices and health insurance companies (Olson 2014). For instance, within the oil corporation *BP*, approximately 14.000 employees opted to wear a free wearable device to monitor their steps in order to reach a predefined objective (i.e. one million steps over the year) in order to obtain a lower insurance premium (Olson 2014).

Lastly, financial incentives appear to be a central element in data-driven health plans: studies which have investigated the application of such programs (e.g. Henkel et al. 2018) have found a prevalence of the use of direct and undirected financial rewards to motivate consumers to subscribe to data-driven health plans (Henkel et al. 2018). These discounts and rewards may take the form of vouchers, cashback, fidelity points, service upgrades or free gifts (Henkel et al. 2018; Hui et al. 2006; Von Entreß-Fürsteneck et al. 2019). Third-party providers may also be involved, with reductions on their products and services (e.g. miles in exchange to airline tickets). Either way, this indicates that health insurance companies often opt for a motivation approach based on external features, which is typically employed when barriers to adoption are perceived as high or when the established goals to achieve are considered as difficult (Norman et al. 2016). This also suggests that the current advantages are still not sufficient to motivate people in using quantified self devices, inducing low opt-in rates (Tedesco et al. 2017). Nonetheless, what is certain is that the use of financial remunerations makes data-driven health plans distinct from any regular complementary coverage or any other health promotion program (Henkel et al. 2018; Martani et al. 2019).

Research Framework

Research Context

In Switzerland health insurance companies are part of a heavily regulated market, where it is made mandatory to every permanent resident to acquire a standard health package from a private health insurer (Swiss Federal Office of Public Health 2019). Individuals are nevertheless free to choose the provider they find appropriate, and fund any additional health care packages (such as data-driven health plans) they find suitable. The whole idea is to maintain a competitive system which assures that the costs of premiums are staying relatively low and that health standards are driving up (Daley et al. 2007). Policies are promoting individual responsibility, consumer control and transparency between all the actors, i.e. health insurance companies, healthcare providers and consumers (Brown 2013; Herzlinger and Parsa-Parsi 2004). It consequently creates space for programs based on quantified self devices. In fact, while health data protection regulation has inhibited these organizations to directly collect highly detailed, health-specific data about their customers (Rosenblat et al. 2014), individuals still have the possibility to upload their biometric information through quantified self devices and share their health reports (Salamati and Pasek 2014). Hence, several Swiss health insurance companies have established data-driven health plans including some sort of quantified self devices device and software for incentivizing a healthier lifestyle, sometimes operating in a grey zone regarding collected health data.

Financial incentives are also largely used as mediums to motivate Swiss consumers to participate in data-driven health plans. Among the five main insurance companies in the country – in terms of insured individuals in 2019 (Swiss Federal Office of Public Health, 2020) – all of them offer a form of financial remuneration to their clients when proposing such programs. Practices vary from reverberating financial gains on healthcare costs, such as a reduction on premiums (e.g. *Helsana)* to delivering vouchers to be spent with one of their partner companies (e.g. *Sanitas*), or providing cashback to clients (e.g. *CSS, Visana*). Table 1 details some of these financial incentives scheme implemented in data-driven health plans in Switzerland.

Health insurance companies	Data-Driven Health Plans	Financial Incentive Schemes
CSS	Mystep	7500 steps to 9999 steps each day enable a credit of CHF 0.20 (¢20); more than 10'000 steps equal to CHF 0.40 (¢40). Credits can be transformed into cashback (CSS 2020).
Helsana	Helsana+	Points are obtained each time the client attain 10000 steps, a pulse rate of 110 per minute for 30 minutes as well as 150 calories burned in 30 minutes. These points can be transformed into discounts or vouchers (Helsana 2020).
Sanitas	Sanitas Active	A daily activity indicator maps the amount of activity done through the day (e.g. steps, natation and biking). Points are collected the daily objective is attained. These points can be transformed into discounts or vouchers (Sanitas 2020).
Swica	Benevita	Points are collected each time a defined goal/challenge is achieved. These points can be transformed into discounts on premium (up to 15%) or vouchers (Swica 2020).
Visana	Mypoints	Points are accounted as soon as the client attain 5000 steps 200 calories burned during the day. These points can be transformed into cashback (Visana 2020).

Table 1. Data-Driven Health Plans in Switzerland

Hypotheses and Constructs Development

To adequately investigate what the effects of financial incentives are regarding the subscription of data-driven health plans, we first review the literature to define how we capture the intention to subscribe to data-driven health plans. We consider this aspect through *use intention,* referring to individual conscious decisions to use a system (De Guinea and Markus 2009). This corresponds to a notion that is systematically used in the Information Systems (IS) literature for approaching the use of a system (De Guinea and Markus 2009; Venkatesh et al. 2003). In fact, following Delone and McLean (2003), use intention communicates an attitude (while use refers more to a behavior, that is often arduous to measure) and thus informs on the likelihood that people use a system. It is therefore considered as an adequate predictive variable for system use (Chen and Cheng 2009).

Next, following our research objective, we assume that financial incentives (e.g. a discount on premiums) increase the proportion of individuals who intend to subscribe to data-driven health plans. As a matter of fact, in a market-oriented health insurance (such as Switzerland, but also Germany or the United States), costs and expenses have a significant impact on choosing and switching between a large panel of private companies (Laske-Aldershof et al. 2004; Thomson et al. 2014). Switzerland notably presents relatively high discrepancies between premiums (even for standard coverage) with health insurance providers distinguishing themselves through discounts, deductibles and particular insurance plans (Daley et al. 2007; Schoen et al. 2010; Thomson et al. 2014). Switching for better offers or preferred care networks is therefore something relatively common: it can be done up to two times a year (Daley et al. 2007) and may attain a rate of 15.4% (2009-2010) among all permanent residents (Thomson et al. 2014). Consistent with this, we posit the following hypothesis:

H1. Financial incentives positively relate to the intention to subscribe to data-driven health plans. The presence of financial incentives increases the intention to subscribe to data-driven health plans.

Moderating factors

To prevent an over-interpretation of the weight of financial incentives as a single factor in the choice of subscribing (or not) to data-driven health plans, we also examine the current literature to uncover the most salient dynamics (alongside financial incentives) that an individual face into subscribing a data-driven health plan in a liberal health insurance market (as in Switzerland). It therefore opens the way to eventual moderating variables that may better explain intention to subscribe to data-driven health plans. It also enables an investigation on eventual significant interactions between financial incentives and other factors.

The literature particularly underlines two dimensions that are dominant in the rationale of choosing a private health insurance company, i.e. consumers' financial capacity and their overall health status (Daley et al. 2007; Schoen et al. 2010).

Earnings and revenue tend to play a big role in consumers' choice regarding insurance scheme, even though Swiss health insurance companies cannot discriminate individuals based on their income (Martani et al. 2019). High income individuals have more opportunities to opt for extra insurance packages and navigate among health insurance companies to target their preferred ones (e.g. health insurance companies that provide data-driven health plans). Further, it is shown that in the consumer market, individuals owning a quantified self device for health promotion are, as a share, persons with higher income, and that they tend to be more active into digital communities (Abril 2016; Ertiö and Räsänen 2019; Régnier and Chauvel 2018). Conversely, individuals with lower income are more cautious in connecting with quantified self devices and engaging in quantified self practices. Early evidence also suggests that white-collar workers (usually individuals with higher incomes) have more possibilities to engage in physical activities than blue-collar workers, because they have more autonomy and flexibility in their workplaces. Thus, they might be in a better position to use quantified self devices effectively and embark onto data-driven health plans (Charitsis 2019; Esmonde and Jette 2018). Hence, we set out to investigate this relation and formulate the hypothesis that individuals with a higher income profile tend to participate more in data-driven health plans.

H2: Income positively relates to the intention to subscribe to data-driven health plans. As income increases, the impact of financial incentives on intention to subscribe to data-driven health plans decreases.

Alongside economic opportunities and financial capacity, the other main factor in the intention of subscribing to health insurance coverages is the perceived health benefits that can be achieved through it. Following the essence of the quantified self-movement, individuals may view quantified self devices as opportunities to scale their physical activity, manage their health levels, and, on the top of that, earn advantages from their health insurer (Paluch and Tuzovic 2019). It may therefore be a way to demonstrate healthy lifestyles (Von Entreß-Fürsteneck et al. 2019); leverage own's low-risk behaviors (Cheung et al. 2016; Paluch and Tuzovic 2019); fix objectives to remain motivated during a long period of time, and even contribute to the "community" with personal data (Cheung et al. 2016). Yet, following Paluch and Tuzovic (2019), individuals that are interested in participating in data-driven health plans express the importance of self-determination: they want to remain in control regarding when to exercise, which information to share and how long to take part in the program. Therefore, we assume that individuals with better health status are more likely to subscribe to data-driven health plans. This idea is further reinforced by the fact that, in a consumer market, individuals that report better health levels (or who do not suffer from chronic illnesses) are also investing more in quantified self devices and quantified self behaviors (Abril 2016). Likewise, individuals with healthy lifestyle patterns frequently perceive and behave in an affirmative way towards new health initiatives (Coulson et al. 1997). Accordingly, we postulate that a better health status is determining for the intention to subscribe to data-driven health plans.

H3: Health status positively relates to the intention to subscribe to data-driven health plans. As the health status increases, the impact of financial incentives on intention to subscribe to data-driven health plans decreases.

In sum, because data-driven health plans are distinctive form any other health insurance coverage plans due to the presence of financial incentives, we get three main factors that presumably influence intention to subscribe to data-driven health plans (i.e. financial incentives, economic conditions and health considerations).

Measurement Development

Investigations on use intention have generally been conducted through quantitative surveys (Delone and McLean 2003), which are considered as appropriate research designs to assure a high generalizability of results (Johnson and Duberley 2000). Accordingly, we opted for a survey in order to gather empirical data and test our research design. More precisely, we conducted a survey in which Swiss permanent residents were asked to explore their intention to subscribe to a data-driven health plan.

To ensure robustness, several iterations of psychometric assessments were done, which resulted in the re-wording or discarding of questions following the discriminant, convergent, and nomological validity of items (see Table 2). All items were asked by means of sliding scales from 0 to 7, with the anchors for all items being 0 = strongly disagree to 7 = strongly agree.

Construct	**Item**	**Description**	**Based on**
Use Intention (UI)	UI1	I wouldn't mind wearing a quantified self device as part of my health plan.	Delone and McLean (2003); Bélanger and Carter (2008); Chen and Cheng (2009) and Pfeiffer et al. (2016)
	UI2	I have no problems in sharing the collected health data of my quantified self device with my health plan provider.	
	UI3	I'm open to using a quantified self device as part of a data-driven health plan.	

Table 2. Measurement Instruments

To assess the weight of financial incentives, two different settings were generated. Within the first, the survey included a discount offer in case of subscription to a data-driven health plan while, in the second setting, no discount offer was proposed. In line with what is being done in Switzerland, the discount proposed in the setting with a financial incentive was a *money per step* scheme, where participants would earn credits (to lower their insurance premium) according to their physical activities.

With regard to previously identified moderating factors that may influence an individual's tendency to subscribe to a data-driven health plan, *income* is corresponding to *available household net income per month*, as it is a standard measure to consider relations with insurance subscriptions (e.g. Schoen et al. 2010). In this study, it was measured on an ordinal scale (1 corresponds to a monthly income < 3000 CHF; 2 a monthly income between 3000 and 6000 CHF; 3 a monthly income of >6000 CHF). For *health status*, a self-rated, ordinal scale was used (1 means that a person has estimated his or her health to be poor; 2 to be neutral; and 3 to be good). As a matter of fact, it is challenging to determine if an individual is in good health, given that it reflects a relative concept which experts continuously redefine and adjust in view of current societal transformations and new medical evidence (Mettler and Wulf 2020). Therefore, self-reported health is a valid and consensually accepted way to overcome this hurdle and measure overall health statuses (Abril 2016; Bowling 2005), being used both in surveys in academic spheres and international organizations (e.g. World Health Organization). For further refinement of the analysis, we also included two control variables: *age* and *gender*. Age was measured on a 3-point ordinal scale with ranges < 25 years, 25 to 55 years, > 55 years and is assumed to have a moderating effect on the intention to subscribe to a data-driven health plan (Morris et al. 2005) as may have gender (Abril 2016), which we measured as a dummy variable (1 referring to female respondents and 0 to male respondents).

The necessary data for testing our hypotheses was obtained by means of an online survey. Respondents for this study were recruited through social media, announcements on our website, as well as by face-to-face recruitment. For reasons of privacy and confidentiality, participants were informed that their answers would remain anonymous and only employed in an academic perspective.

Profile of the Sample

Participants were randomly assigned to one of the two groups, with a sample of 223 valid responses for the survey with the discount offer and 218 valid responses for the survey without discount (see Table 3). Note that only full records (without missing data) were included into analysis. Out of the sample with a discount offer, 48.8% were male and 51.1% female. As regards the age of the respondents, 53.4% were below 25 years, 30.9% between 25 and 55, and 15.7% older than 55 years. 43.1% declared themselves to be in excellent health, 11.9% in reasonable health, and 9.4% expressed to be in rather poor health conditions. From a financial perspective, 54.7% had less than 3,000 CHF a month in disposable income, 39.0% between 3,000 and 6,000 CHF, and 6.3% a monthly budget of more than 6,000 CHF. For the sample without discount, relatively similar numbers were obtained: 51.8% were female, 48.2% male; 44.0% were younger than 25 years, 33.0% were between 25 and 55 and 23.0% were more than 55 years old. 16.1% declared having a rather poor health, 39.0% reasonable health conditions and 45.9% good health levels. Lastly, 42.2% expressed having a household net income below 3000 CHF, 36.2% between 3,000 and 6,000 CHF, and 21.6% a monthly budget of more than 6,000 CHF.

	With discount (n=223)	**Without discount (n=218)**
Gender	109F (48.8%), 114M (51.1%)	113F (51.8%), 105M (48.2%)
Age (<25|25-55|>55)	119 (53.4%), 69 (30.9%), 35 (15.7%)	96 (44.0%), 72 (33.0%), 50 (23.0%)
Income (<3k|3k-6k|>6k CHF)	122 (54.7%), 87 (39.0%), 14 (6.3%)	92 (42.2%), 79 (36.2%), 47 (21.6%)
Health (poor|neutral|good)	21 (9.4%), 106 (47.5%), 96 (43.1%)	35 (16.1%), 85 (39.0%), 98 (45.9%)

Table 3. Descriptive Statistics of Survey Experiment

Data Analysis

An analysis of variance (ANOVA) was performed to test the main between-subjects effects, using *Stata version 14.2*. Results of the analysis can be found in Table 4.

First, from the F-statistic, we identified that the main effect *discount* reached a significant level (F=13.37, Sig. 0.0). Main effects *income* (Sig. 0.10) and *health* (Sig. 0.24) are not found to be statistically significant, as probabilities for both are more than the standard significance level of 0.05. Second, as regards interaction effects, only the crossover *interaction discount×income×health* is found to be statistically significative (Sig.0.05). The effects of *income* and *health* only exist over levels of *discount*.

It therefore means that only H1 is supported, whereas H2 and H3 are rejected.

Source	**df**	**Mean square**	**F**	**Sig.**
Discount	1	15.86	13.73	0.00
Income	2	2.63	2.28	0.10
Health	2	1.65	1.43	0.24
Discount×income	2	0.58	0.50	0.61
Income×health	4	1.32	1.14	0.33
Discount×health	2	1.66	1.44	0.24
Discount×income×health	4	2.69	2.33	0.05

Table 4. ANOVA Test –Main and Interaction Effects

To better visualize the interplay between *discount*, *income* and *health*, we graphed in Figure 1 the relationships between these 3 factors. In accordance with our sliding scale employed for use intention, we also delineated into thirds areas regarding individual intention to use data-driven health plans (i.e. *no-go area*, from 0 to 2.33; *reflection area*, from 2.34 to 4.66 and *definitive use area*, from 4.67 to 7).

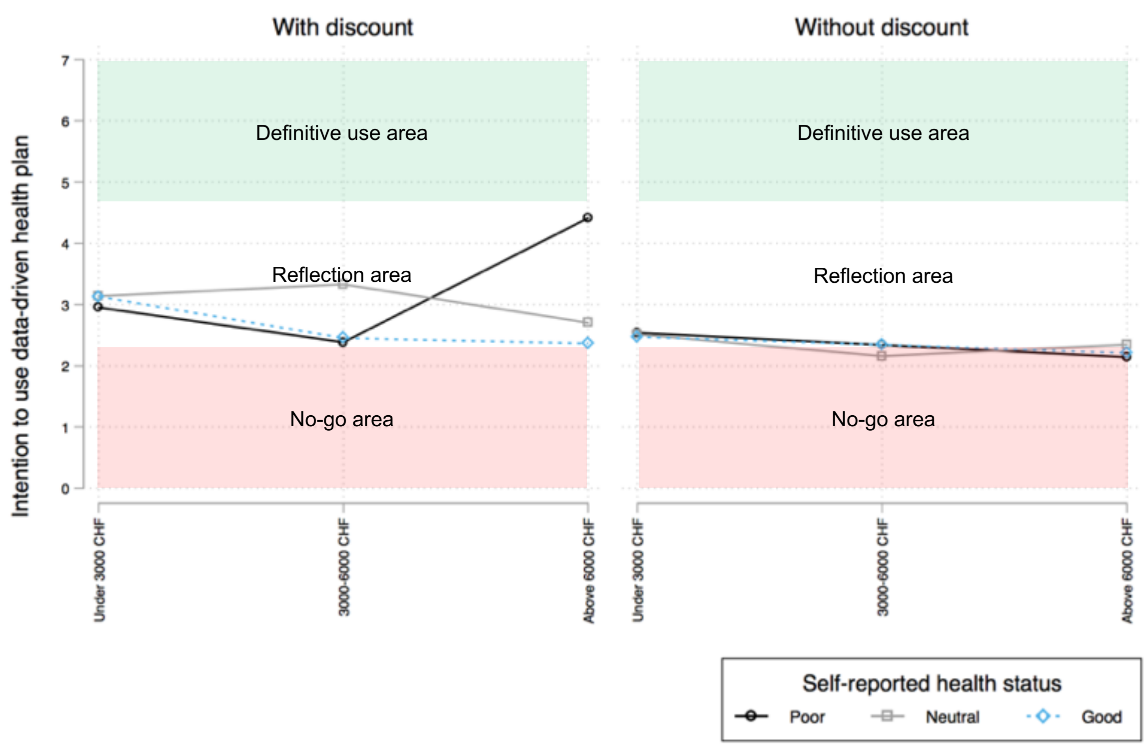

Figure 1. Interaction Effects *discount*×*income*×*health* on Intention to Use Data-Driven Health Plans

Discussion

First, the findings of the present study underline the importance of financial incentives to motivate consumers to subscribe to data-driven health plans, as the intention to use quantified self devices is significantly associated with the presence of discounts. Data-driven health plans that include such bonuses, which are often emphasized by the institution (Henkel et al. 2018; Von Entreß-Fürsteneck et al. 2019), have an increased likelihood of consumers' participation compared to data-driven health plans with no discount. Some individuals are consequently perceiving the use of quantified self devices under a utilitarian and functional perspective: the discount acts as an extrinsic factor that triggers the motivation (Ryan and Deci 2000). This is in line with conclusions drawn by the literature about the use quantified self devices in consumer settings, as the role of external factors (e.g. discounts, rewards) is acknowledged to prompt adoption (Mekler et al. 2017; Shin et al. 2015). These external motivators therefore serve as proxies to reduce the costs of engaging into the early stage of use of quantified self devices (Attig et al. 2018; Munson 2017; Rapp and Cena 2014). The same phenomena can be also found in organizational settings, especially in contexts where the employer is providing health insurance to employees (Olson 2015; Suh et al. 2017). For instance, within the oil corporation *BP*, approximately 14.000 employees have opted to wear a free wearable device to monitor their steps in order to reach a predefined objective (i.e. one million steps over the year) in order to obtain a lower insurance premium (Olson 2014).

Second, in the scenario where discounts are not included, income or perceived health levels do not exercise a particular effect on the intention to subscribe to data-driven health plans. In this regard, our findings do not resonate with evidence from commercial use, as (1) Ertiö and Räsänen (2019) found that the most salient contextual factor in purchasing quantified self devices was income; while (2) Abril (2016) indicated that consumers with better health levels tended to invest more in quantified self devices. Moreover, without the presence of a discount, use intention remains low among the wider audience (even reaching the *no-go area*). This confirms that the promises of health improvement are still not sufficient to motivate people to use quantified self devices provided by health insurance companies. It may also illustrate that concerns about these programs are still very prevalent. As mentioned earlier, first studies on data-driven health plans have mainly assessed privacy challenges regarding individual adoption. In particular, they have determined that potential security breaches, disruption of private life, fear of a discrimination based on health levels and unwanted targeted marketing have been the key individual concerns regarding the use of quantified self devices in data-driven health plans (Cheung et al. 2016; Paluch and Tuzovic 2019; Patterson 2013; Von Entreß-Fürsteneck et al. 2019). Likewise, perceived data sensitivity has been found to exercise a moderating effect on this risk-benefits analysis, with a willingness to share data being more predominant for data such as steps or distance walked, and less for information such as heart rate or rhythm, blood pressure or weight (Von Entreß-Fürsteneck et al. 2019). Hence, the role of financial incentives are still fundamental for health insurance companies to overcome these barriers and attract more than a small proportion of early adopters, which are found to be more risk-tolerant (Cheung et al. 2016). These are usually highly motivated, computer literate and tech savvy individuals that are moved by a determined wish for self-improvement and a curiosity for detailed personal information (Ancker et al. 2015; Whooley et al. 2014), but that do not represent in any way the rest of the population.

This naturally brings us to take a more precise look on the proportion of increase in use intention that financial incentives induce and, then, eventually define typical profiles where this increase is more perceptible. The existence of a discount mechanism overall increases intention to subscribe to data-driven health plans among all types of profiles (notably moving all patterns outside the *no-go area*). Still, for a majority of cases, this represents a marginal growth in intention, showing that a certain amount of skepticism remains towards institutions providing data-tracking technologies (Cheung et al. 2016; Mettler and Wulf 2019; Patterson 2013).

In two combinations, however, this increase in use intention is more pronounced. First, individuals with lower income, regardless of their health status, are more inclined to subscribe to data-driven health plans with discounts. This may be the expression of an engagement out of financial need: the incentive acts as a trigger and engenders a trade-off between data sharing and financial benefit (Veale 2018). Second, consumers with a high income and a perceived poor health status show a noticeable increase in use intention. Such a result might appear surprising at first, as the general comprehension is that individuals with good perceived health status may be driven by a need to demonstrate their good health habits and gain recognition for their capabilities in self-management (Hardey 2019). However, providing access to quantified self practices might also be apprehended by some as an occasion to improve their health levels (Patterson 2013; Spender et al. 2019). This dichotomy truly illustrates the ambivalent nature of quantified self practices: at the same time, they may represent opportunities and challenges in terms of health promotion; thus it is often according to a particular situation that one of these dimensions emerges (Lavallière et al. 2016; Majmudar et al. 2015; West et al. 2016). For our particular case, we can argue that high income individuals have, in theory, more flexibility into contracting additional coverages, which means that they are primarily interested into enhancing their health levels. In fact, some studies suggest that a considerable share of individuals with perceived poor health status are willing to make their information visible. They do so to either motivate themselves (Nelson et al. 2016) and/or receive quality healthcare (Kordzadeh and Warren 2014). Put differently, they are often the ones that value the most the accessibility and availability of health data (Lafky and Horan 2011).

Finally, the fact that financial incentives have a significant impact on use intention might raise questions about the role of this reward in the relation between health insurance companies and consumers. For instance, some may argue that it creates an environment of *indirect coercion* on consumers (Rieder 2015; Stepanchuk 2017), as it may give the impression to individuals that they are high downsides on refusing the discount and the subscription. It may notably induce the feeling that they are missing an opportunity to spare money, that they are putting themselves in position to pay a higher health premiums than others, that they do not have the same opportunities as people that exercise often or that they are discriminated based on their health condition (Paluch and Tuzovic 2019; Rieder 2015). As a result, offering financial incentives in data-driven health plans may call for a new form of regulation of the health system in order to maintain social solidarity among consumers (Martani et al. 2019; Paluch and Tuzovic 2019; Rieder 2015). It may thus generate a source of tension between individual responsibility and solidarity, distorting the perception of individual duty, consumer control and transparency between all the actors, i.e. health insurance companies, healthcare providers and consumers (Brown 2013; Herzlinger and Parsa-Parsi 2004; Martani et al. 2019).

Limitations and Future Research

Certainly, this study has several limitations. First, it is based on hypothetical scenarios that are necessarily rooted in a context. In Switzerland, people are considerably vigilant and regardful of healthcare costs and means of diminishing these costs (Schindler et al. 2018), because it represents for most Swiss residents the greatest share of household expenditure (i.e. compulsory health insurance and extra coverages). Therefore, individuals are rather proactive in migrating between health insurance companies, which might be different than in other cultural contexts or societies. Similarly, we have developed our research framework (and independent variables) on the basis of the assumption of a liberal market with choice options. Although this form of healthcare system is common in industrialized countries, researchers and practitioners should always be aware of their particular context to assess the applicability of our outline and accordingly adapt to the specificities of their situation.

Next, we intend, through this work, to lay the foundations for better understanding the role of financial incentives in consumers' choice regarding subscription to data-driven health plans. While we provide a precise direction, future work could use more granularity in the level of analysis. For instance, we have unveiled that perceived health levels might influence intention to subscribe to data-driven health plans (for individuals with high income and in the presence of discount): yet, we presume that it might the case for individuals that perceive their health as poor but do not suffer from a chronic disease. In fact, we base such assumption upon evidence from commercial use: Paré et al. (2018) reveal that there is no statistically significant difference between groups in perceived health levels in the use of quantified self devices, whereas individuals suffering from a chronic condition have less chance to engage with the use of quantified self devices.

Nonetheless, this also illustrates the large possible avenues and opportunities for further research. In particular, qualitative studies may help to complete the profile of individuals that participate in data-driven health plans, providing a more nuanced view of the overall population (Levine et al. 2017). As use is a behavior, it is often more complex than a an intention, which is driven by a small number of independent and defined variables (Lippke et al. 2015). Thus, use experiences, familiarity with technology, habits, emotions have also an important effect of observed IS use (Beaudry and Pinsonneault 2010; Polites and Karahanna 2013; Stepanovic et al. 2019; Van der Heijden 2004). In particular, they allow to expose different patterns than demographic characteristics, since they are not detected with typical survey-based studies (Mettler and Wulf 2019).

Furthermore, investigating continuation patterns and long-term engagement with quantified self devices sponsored by health insurance companies is crucial. Quantified self instruments have to be, in principle, used in a continuous manner to generate records and information to both support individuals' health empowerment and provide health insurance companies with relevant data. The following step subsequently lies in understanding if financial incentives also engender a long-term participation. Early evidence in consumer or organizational settings tend to show that involvement in quantified self practices is not necessarily assured with the presence of discounts or rewards. For example, Hunter et al. (2016) report that there they did not found any significant difference between control and intervention groups in terms of minutes of physical activity recorded (after 3 months and 6 months) in a workplace health program. Similarly, Spender et al. (2019) indicate that they had no confirmations of change in long-term health behavior, even in clinician-led health intervention plans.

Finally, another interesting opportunity to continue this reflection is to examine how consumers perceive financial incentives provided by third-party entities. While we have mentioned the general distrust among the population regarding data-driven health plans, some researchers argue that the presence of a financial reward is a form of confession on the uselessness and unpleasantness for the consumers (Maturo and Setiffi 2016; Morozov 2013) and that the use quantified self devices in these plans is directly conflicting with consumers interests. There is therefore a high potential to consider their use in other settings (e.g. at the workplace) as well as explore ethical sides regarding such ubiquitous technology and the potential economization of data. In particular, investigations regarding the fairness in offering financial retribution in exchange of access to individual data or the moral obligation for individuals to participate in data-driven programs sponsored by third-party entities may be interesting avenues for research.

Conclusion

Some scholars indicate that quantified self devices are becoming a new paradigm for many health insurance companies around the globe (Martani et al. 2019). While there is a general buzz and interest among these companies, as well as among researchers, public institutions and mass media (Silvello and Procaccini 2019), very little is known about mechanisms, such as financial incentives, that drive individuals to subscribe to data-driven health plans. To address this lack of generalizable findings, we report results from a survey made in Switzerland, which represents a context of typical consumers' choice in a liberal health insurance market.

Our results notably unveil that financial incentives significantly impact intention to use quantified self devices provided by health insurance companies. They especially drive more interest from individuals with a high income and a perceived poor health status. This shed light on the importance of opportunity that these plans correspond for consumers. We argue that financial incentives increase the perception of a chance to gain financial retribution or improve a poor health level with a plan that is otherwise (without discount) not particularly appealing for the wider population. Likewise, we identify elements that allow to continue the reflection on individual characteristics, mindsets and motivations to participate in data-driven health plans and propose potential avenues for further research. We accordingly hope to provide a solid basis on which researchers might continue investigating a topic that is gaining a high relevance.

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References

Abril, E. P. 2016. "Tracking Myself: Assessing the Contribution of Mobile Technologies for Self-Trackers of Weight, Diet, or Exercise," *Journal of Health Communication* (21:6), pp. 638-646.

Accenture. 2015. "Digital Insurance Era: Stretch Your Boundaries" Retrieved on April 30, 2020 from https://www.accenture.com/_acnmedia/pdf-51/accenture-technology-vision-for-insurance-2015-full-report-pov.pdf

Ajana, B. 2017. "Digital Health and the Biopolitics of the Quantified Self," *Digital Health* (3), pp. 1-18.

Ancker, J. S., Witteman, H. O., Hafeez, B., Provencher, T., Van de Graaf, M., and Wei, E. 2015. "You Get Reminded You're a Sick Person": Personal Data Tracking and Patients with Multiple Chronic Conditions," *Journal of Medical Internet Research* (17:8), pp. 1-12.

Appelboom, G., Camacho, E., Abraham, M. E., Bruce, S. S., Dumont, E. L., Zacharia, B. E., D'Amico, R., Slomian, J., Reginster, J. Y., and Bruyère, O. 2014. "Smart Wearable Body Sensors for Patient Self-Assessment and Monitoring," *Archives of Public Health* (72:28), pp. 1-9.

Attig, C., Karp, A., and Franke, T. 2018. "User Diversity in the Motivation for Wearable Activity Tracking: A Predictor for Usage Intensity?," in *Proceedings of the 20th Congress of the International Ergonomics Association*, Florence, Italy, pp. 431-440.

Beaudry, A., and Pinsonneault, A. 2010. "The Other Side of Acceptance: Studying the Direct and Indirect Effects of Emotions on Information Technology Use," *MIS Quarterly* (34:4), pp. 689-710.

Bélanger, F., and Carter, L. 2008. "Trust and Risk in E-Government Adoption," *The Journal of Strategic Information Systems* (17:2), pp. 165-176.

Bowling, A. 2005. "Mode of Questionnaire Administration Can Have Serious Effects on Data Quality," *Journal of Public Health* (27:3), pp. 281-291.

Brown, R. C. 2013. "Moral Responsibility for (Un) Healthy Behaviour," *Journal of Medical Ethics* (39:11), pp. 695-698.

Buchwald, A., Letner, A., Urbach, N., and von Entress-Fuersteneck, M. 2015. "Towards Explaining the Use of Self-Tracking Devices: Conceptual Development of a Continuance and Discontinuance Model," in *Proceedings of the 36th International Conference on Information Systems* Forth Worth, USA, pp. 1-12.

Canhoto, A. I., and Arp, S. 2017. "Exploring the Factors That Support Adoption and Sustained Use of Health and Fitness Wearables," *Journal of Marketing Management* (33:1-2), pp. 32-60.

Charitsis, V. 2019. "Survival of the (Data) Fit: Self-Surveillance, Corporate Wellness, and the Platformization of Healthcare," *Surveillance & Society* (17:1/2), pp. 139-144.

Chen, C.-W. D., and Cheng, C.-Y. J. 2009. "Understanding Consumer Intention in Online Shopping: A Respecification and Validation of the Delone and Mclean Model," *Behaviour & Information Technology* (28:4), pp. 335-345.

Cheung, C., Bietz, M. J., Patrick, K., and Bloss, C. S. 2016. "Privacy Attitudes among Early Adopters of Emerging Health Technologies," *PLOS ONE* (11:11), pp. 1-12.

Choe, E. K., Lee, N. B., Lee, B., Pratt, W., and Kientz, J. A. 2014. "Understanding Quantified-Selfers' Practices in Collecting and Exploring Personal Data," in *Proceedings of the 32nd annual ACM Conference on Human Factors in Computing Systems*, Toronto, Canada, pp. 1143-1152.

Choe, Y., and Fesenmaier, D. R. 2017. "The Quantified Traveler: Implications for Smart Tourism Development," in *Analytics in Smart Tourism Design*. Springer, Cham, pp. 65-77.

Constantiou, I. D., and Kallinikos, J. 2015. "New Games, New Rules: Big Data and the Changing Context of Strategy," *Journal of Information Technology* (30:1), pp. 44-57.

Coulson, N., Eiser, C., and Eiser, J. 1997. "Diet, Smoking and Exercise: Interrelationships between Adolescent Health Behaviours," *Child: Care, Health and Development* (23:3), pp. 207-216.

CSS. 2020. "Mystep - Chaque Pas Compte " Retrieved on April 30, 2020 from https://www.css.ch/fr/home/privatpersonen/kontakt_service/mycss/mystep.html

Daley, C., Gubb, J., Clarke, E., and Bidgood, E. 2007. "Healthcare Systems: Switzerland," *Civitas Health Unit* (1), pp. 1-15.

Dargazany, A. R., Stegagno, P., and Mankodiya, K. 2018. "Wearable Dl: Wearable Internet-of-Things and Deep Learning for Big Data Analytics—Concept, Literature, and Future," *Mobile Information Systems* (2018), pp. 1-20.

De Guinea, A. O., and Markus, M. L. 2009. "Why Break the Habit of a Lifetime? Rethinking the Roles of Intention, Habit, and Emotion in Continuing Information Technology Use," *MIS Quarterly* (33:3), pp. 433-444.

De Moya, J.-F., and Pallud, J. 2017. "Quantified Self: A Literature Review Based on the Funnel Paradigm," in *Proceedings of the 25th European Conference on Information Systems*, Guimares, Portugal.

Delone, W. H., and McLean, E. R. 2003. "The Delone and Mclean Model of Information Systems Success: A Ten-Year Update," *Journal of Management Information Systems* (19:4), pp. 9-30.

Didžiokaitė, G., Saukko, P., and Greiffenhagen, C. 2018. "The Mundane Experience of Everyday Calorie Trackers: Beyond the Metaphor of Quantified Self," *New Media & Society* (20:4), pp. 1470-1487.

Epstein, D. A., Ping, A., Fogarty, J., and Munson, S. A. 2015. "A Lived Informatics Model of Personal Informatics," in *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, New York, USA, pp. 731-742.

Ertiö, T., and Räsänen, P. 2019. "Consumerism in Online Health Information Search and Self-Tracking Devices," *International Journal of Consumer Studies* (43:3), pp. 245-252.

Esmonde, K., and Jette, S. 2018. "Fatness, Fitness, and Feminism in the Built Environment: Bringing Together Physical Cultural Studies and Sociomaterialisms, to Study the “Obesogenic Environment”," *Sociology of Sport Journal* (35:1), pp. 39-48.

Glaros, C., and Fotiadis, D. I. 2005. "Wearable Devices in Healthcare," in *Intelligent Paradigms for Healthcare Enterprises*. Springer, Heidelberg, pp. 237-264.

Gorm, N. 2017. "Personal Health Tracking Technologies in Practice," in *Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing*, Portland, USA, pp. 69-72.

Hardey, M. 2019. "On the Body of the Consumer: Performance-Seeking with Wearables and Health and Fitness Apps," *Sociology of Health & Illness* (1), pp. 1-14.

Helsana. 2020. "Nous Récompensons Votre Mode De Vie Sain. Avec L'app Helsana+" Retrieved on April 30, 2020 from https://www.helsana.ch/microsite/plus/#/

Henkel, M., Heck, T., and Göretz, J. 2018. "Rewarding Fitness Tracking—the Communication and Promotion of Health Insurers' Bonus Programs and the Use of Self-Tracking Data," in *Proceedings of the 2018 International Conference on Social Computing and Social Media*, Las Vegas, USA, pp. 28-49.
Herzlinger, R. E., and Parsa-Parsi, R. 2004. "Consumer-Driven Health Care: Lessons from Switzerland," *Journal of American Medical Association* (292:10), pp. 1213-1220.
Heyen, N. B. 2016. "Self-Tracking as Knowledge Production: Quantified Self between Prosumption and Citizen Science," in *Lifelogging*, S. Selke (ed.), Wiesbaden: Springer, pp. 283-301.
Hui, K.-L., Tan, B. C., and Goh, C.-Y. 2006. "Online Information Disclosure: Motivators and Measurements," *ACM Transactions on Internet Technology* (6:4), pp. 415-441.
Hunter, R. F., Brennan, S. F., Tang, J., Smith, O. J., Murray, J., Tully, M. A., Patterson, C., Longo, A., Hutchinson, G., and Prior, L. 2016. "Effectiveness and Cost-Effectiveness of a Physical Activity Loyalty Scheme for Behaviour Change Maintenance: A Cluster Randomised Controlled Trial," *BMC Public Health* (16:1), p. 618.
Johnson, P., and Duberley, J. 2000. *Understanding Management Research: An Introduction to Epistemology*. Thousand Oaks: Sage.
Karkar, R., Zia, J., Vilardaga, R., Mishra, S. R., Fogarty, J., Munson, S. A., and Kientz, J. A. 2015. "A Framework for Self-Experimentation in Personalized Health," *Journal of the American Medical Informatics Association* (23:3), pp. 440-448.
Kim, J. 2014. "A Qualitative Analysis of User Experiences with a Self-Tracker for Activity, Sleep, and Diet," *Interactive Journal of Medical Research* (3:1), pp. 1-9.
King, A. C., Glanz, K., and Patrick, K. 2015. "Technologies to Measure and Modify Physical Activity and Eating Environments," *American Journal of Preventive Medicine* (48:5), pp. 630-638.
Kordzadeh, N., and Warren, J. 2014. "Personal Characteristics, Privacy Concern, and Membership in Virtual Health Communities: An Empirical Study," in *Proceedings of the 20th Americas Conference on Information Systems*, Savannah, USA, pp. 1-10.
Lafky, D. B., and Horan, T. A. 2011. "Personal Health Records: Consumer Attitudes toward Privacy and Security of Their Personal Health Information," *Health Informatics Journal* (17:1), pp. 63-71.
Laske-Aldershof, T., Schut, E., Beck, K., Greß, S., Shmueli, A., and Van de Voorde, C. 2004. "Consumer Mobility in Social Health Insurance Markets," *Applied Health Economics and Health Policy* (3:4), pp. 229-241.
Lavallière, M., Burstein, A. A., Arezes, P., and Coughlin, J. F. 2016. "Tackling the Challenges of an Aging Workforce with the Use of Wearable Technologies and the Quantified-Self," *DYNA* (83:197), pp. 38-43.
Levine, D. M., Lipsitz, S. R., and Linder, J. A. 2017. "Changes in Everyday and Digital Health Technology Use among Seniors in Declining Health," *The Journals of Gerontology: Series A* (73:4), pp. 552-559.
Lewalle, H. 2006. "A Look at Private Health Care Insurance in the European Union," *Revue Française des Affaires Sociales* (1:6), pp. 133-157.
Li, H., Wu, J., Gao, Y., and Shi, Y. 2016. "Examining Individuals' Adoption of Healthcare Wearable Devices: An Empirical Study from Privacy Calculus Perspective," *International Journal of Medical Informatics* (88), pp. 8-17.
Li, I., Dey, A., Forlizzi, J., Höök, K., and Medynskiy, Y. 2011. "Personal Informatics and Hci: Design, Theory, and Social Implications," in *Proceedings of the 2011 Conference on Human Factors in Computing Systems*, Vancouver, Canada, pp. 2417-2420.
Lippke, S., Fleig, L., Wiedemann, A. U., and Schwarzer, R. 2015. "A Computerized Lifestyle Application to Promote Multiple Health Behaviors at the Workplace: Testing Its Behavioral and Psychological Effects," *Journal of Medical Internet Research* (17:10), pp. 1-19.
Lupton, D. 2014a. "Health Promotion in the Digital Era: A Critical Commentary," *Health Promotion International* (30:1), pp. 174-183.
Lupton, D. 2014b. "Self-Tracking Cultures: Towards a Sociology of Personal Informatics," in *Proceedings of the 26th Australian Computer-human interaction conference on designing futures: The future of design*, Sydney, Australia, pp. 77-86.
Lupton, D. 2014c. "Self-Tracking Modes: Reflexive Self-Monitoring and Data Practices," in *Proceedings of the 2015 Social Life of Big Data Symposium*, Perth, Australia, pp. 1-19.
Lupton, D. 2016. "The Diverse Domains of Quantified Selves: Self-Tracking Modes and Dataveillance," *Economy and Society* (45:1), pp. 101-122.
Majmudar, M. D., Colucci, L. A., and Landman, A. B. 2015. "The Quantified Patient of the Future: Opportunities and Challenges," *Healthcare* (3:3), pp. 153-156.

Marakhimov, A., and Joo, J. 2017. "Consumer Adaptation and Infusion of Wearable Devices for Healthcare," *Computers in Human Behavior* (76), pp. 135-148.

Martani, A., Shaw, D., and Elger, B. S. 2019. "Stay Fit or Get Bit-Ethical Issues in Sharing Health Data with Insurers' Apps," *Swiss Medical Weekly* (149:2526), pp. 1-8.

Maturo, A., and Setiffi, F. 2016. "The Gamification of Risk: How Health Apps Foster Self-Confidence and Why This Is Not Enough," *Health, Risk & Society* (17:7-8), pp. 477-494.

Meißner, S. 2016. "Effects of Quantified Self Beyond Self-Optimization," in *Lifelogging*, S. Selke (ed.), Wiesbaden: Springer, pp. 235-248.

Mekler, E. D., Brithlmann, F., Tuch, A. N., and Opwis, K. 2017. "Towards Understanding the Effects of Individual Gamification Elements on Intrinsic Motivation and Performance," *Computers in Human Behavior* (71), pp. 525-534.

Mettler, T., and Wulf, J. 2019. "Physiolytics at the Workplace: Affordances and Constraints of Wearables Use from an Employee's Perspective," *Information Systems Journal* (29:1), pp. 1-29.

Mettler, T., and Wulf, J. 2020. "Health Promotion with Physiolytics: What Is Driving People to Subscribe in a Data-Driven Health Plan," *PLOS ONE* (15:4), pp. 1-19.

Mills, A. J., Watson, R. T., Pitt, L., and Kietzmann, J. 2016. "Wearing Safe: Physical and Informational Security in the Age of the Wearable Device," *Business Horizons* (59:6), pp. 615-622.

Morozov, E. 2013. *To Save Everything, Click Here: The Folly of Technological Solutionism*. Public Affairs, New York.

Morris, M. G., Venkatesh, V., and Ackerman, P. L. 2005. "Gender and Age Differences in Employee Decisions About New Technology: An Extension to the Theory of Planned Behavior," *IEEE Transactions on Engineering Management* (52:1), pp. 69-84.

Munson, S. A. 2017. "Rethinking Assumptions in the Design of Health and Wellness Tracking Tools," *Interactions* (25:1), pp. 62-65.

Nelson, E. C., Verhagen, T., and Noordzij, M. L. 2016. "Health Empowerment through Activity Trackers: An Empirical Smart Wristband Study," *Computers in Human Behavior* (62), pp. 364-374.

Norman, G. J., Heltemes, K. J., Heck, D., and Osmick, M. J. 2016. "Employee Use of a Wireless Physical Activity Tracker within Two Incentive Designs at One Company," *Population Health Management* (19:2), pp. 88-94.

Olson, P. 2014. "Wearable Tech Is Plugging into Health Insurance" Retrieved on April 30, 2020 from http://www.forbes.com/sites/parmyolson/2014/06/19/wearable-tech-health-insurance/

Olson, P. 2015. "More Bosses Expected to Track Their Staff through Wearables in the Next 5 Years " Retrieved on April 30, 2020 from https://www.forbes.com/sites/parmyolson/2015/06/01/wearables-employee-tracking/

Paluch, S., and Tuzovic, S. 2019. "Persuaded Self-Tracking with Wearable Technology: Carrot or Stick?," *Journal of Services Marketing* (33:4), pp. 436-448.

Paré, G., Leaver, C., and Bourget, C. 2018. "Diffusion of the Digital Health Self-Tracking Movement in Canada: Results of a National Survey," *Journal of Medical Internet Research* (20:5), pp. 1-16.

Patterson, H. 2013. "Contextual Expectations of Privacy in Self-Generated Health Information Flows," in *Proceedings of the 41st Research Conference on Communication, Information and Internet Policy*, Arlington, USA, pp. 1-48.

Pfeiffer, J., von Entress-Fuersteneck, M., Urbach, N., and Buchwald, A. 2016. "Quantify-Me: Consumer Acceptance of Wearable Self-Tracking Devices," in *Proceedings of the 24th European Conference on Information Systems,* Istanbul, Turkey, pp. 1-15.

Piwek, L., Ellis, D. A., Andrews, S., and Joinson, A. 2016. "The Rise of Consumer Health Wearables: Promises and Barriers," *PLOS Medicine* (13:2), pp. 1-9.

Polites, G. L., and Karahanna, E. 2013. "The Embeddedness of Information Systems Habits in Organizational and Individual Level Routines: Development and Disruption," *MIS Quarterly* (37:1), pp. 221-246.

Rapp, A., and Cena, F. 2014. "Self-Monitoring and Technology: Challenges and Open Issues in Personal Informatics," in *Proceedings of the 2014 International Conference on Universal Access in Human-Computer Interaction*, Heraklion, Greece, pp. 613-622.

Régnier, F., and Chauvel, L. 2018. "Digital Inequalities in the Use of Self-Tracking Diet and Fitness Apps: Interview Study on the Influence of Social, Economic, and Cultural Factors," *Journal of Medical Internet Research mHealth and uHealth* (6:4), pp. 1-13.

Rieder, A. 2015. "Health and Everyday Life: The Potential of Self-Monitoring in Managing the Own Health," *in the Internet of Things Era* (1), pp. 70-77.

Rooksby, J., Rost, M., Morrison, A., and Chalmers, M. C. 2014. "Personal Tracking as Lived Informatics," in *Proceedings of the 32nd annual ACM Conference On Human Factors in Computing Systems*, Toronto, Canada, pp. 1163-1172.

Rosenblat, A., Wikelius, K., Gangadharan, S. P., and Yu, C. 2014. "Data & Civil Rights: Health Primer," in *Proceedings of the 2014 Data & Civil Rights Conference*, Washington DC, USA, pp. 1-9.

Ruckenstein, M., and Pantzar, M. 2017. "Beyond the Quantified Self: Thematic Exploration of a Dataistic Paradigm," *New Media & Society* (19:3), pp. 401-418.

Ryan, R. M., and Deci, E. L. 2000. "Intrinsic and Extrinsic Motivations: Classic Definitions and New Directions," *Contemporary Educational Psychology* (25:1), pp. 54-67.

Salamati, F., and Pasek, Z. J. 2014. "Personal Wellness: Complex and Elusive Product and Distributed Self-Services," *Procedia CIRP* (16), pp. 283-288.

Samuel, R. E., and Connolly, D. 2015. "Internet of Things-Based Health Monitoring and Management Domain-Specific Architecture Pattern," *Issues in Information Systems* (16:4), pp. 58-63.

Sanitas. 2020. "Sanitas Active App" Retrieved on April 30, 2020 from https://www.sanitas.com/fr/clients-prives/contact-et-aide/portail-clients-et-applis/appli-active.html

Schindler, M., Danis, M., Goold, S. D., and Hurst, S. A. 2018. "Solidarity and Cost Management: Swiss Citizens' Reasons for Priorities Regarding Health Insurance Coverage," *Health Expectations* (21:5), pp. 858-869.

Schoen, C., Osborn, R., Squires, D., Doty, M. M., Pierson, R., and Applebaum, S. 2010. "How Health Insurance Design Affects Access to Care and Costs, by Income, in Eleven Countries," *Health Affairs* (29:12), pp. 2323-2334.

Shin, D.-H., and Biocca, F. 2017. "Health Experience Model of Personal Informatics: The Case of a Quantified Self," *Computers in Human Behavior* (69), pp. 62-74.

Shin, G., Cheon, E. J., and Jarrahi, M. H. 2015. "Understanding Quantified-Selfers' Interplay between Intrinsic and Extrinsic Motivation in the Use of Activity-Tracking Devices," in *Proceedings of the 2015 iConference* New Port Beach, USA, pp. 1-3.

Silvello, A., and Procaccini, A. 2019. "Connected Insurance Reshaping the Health Insurance Industry," in *Smart Healthcare*. London: IntechOpen, pp. 1-12.

Spender, A., Bullen, C., Altmann-Richer, L., Cripps, J., Duffy, R., Falkous, C., Farrell, M., Horn, T., Wigzell, J., and Yeap, W. 2019. "Wearables and the Internet of Things: Considerations for the Life and Health Insurance Industry," *British Actuarial Journal* (24), pp. 1-31.

Stepanchuk, Y. 2017. "Quantified Construction of Self: Numbers, Narratives and the Modern Individual," in *Proceedings of the 2017 International Conference Ion Internet and Modern Society*, St. Petersburg, Russia, pp. 28-36.

Stepanovic, S., Mettler, T., Schmidt-Kraepelin, M., Thiebes, S., and Sunyaev, A. 2019. "Wearable Health Devices in the Workplace: The Importance of Habits to Sustain the Use," in *Proceedings of the 21st IEEE Conference on Business Informatics*, Moscow, Russia, pp. 1-10.

Suh, A., Cheung, C. M. K., Ahuja, M., and Wagner, C. 2017. "Gamification in the Workplace: The Central Role of the Aesthetic Experience," *Journal of Management Information Systems* (34:1), pp. 268-305.

Swan, M. 2012a. "Health 2050: The Realization of Personalized Medicine through Crowdsourcing, the Quantified Self, and the Participatory Biocitizen," *Journal of Personalized Medicine* (2:3), pp. 93-118.

Swan, M. 2012b. "Sensor Mania! The Internet of Things, Wearable Computing, Objective Metrics, and the Quantified Self 2.0," *Journal of Sensor and Actuator Networks* (1:3), pp. 217-253.

Swan, M. 2013. "The Quantified Self: Fundamental Disruption in Big Data Science and Biological Discovery," *Big Data* (1:2), pp. 85-99.

Swica. 2020. "Benevita" Retrieved on April 30, 2020, from https//www.benevita.ch

Swiss Federal Office of Public Health. 2018. "Directories of Approved Health Insurers and Reinsurers" Retrieved on April 30, 2020 from https://www.bag.admin.ch/bag/en/home/versicherungen/krankenversicherung/krankenversicherung-versicherer-aufsicht/verzeichnisse-krankenundrueckversicherer.html

Tedesco, S., Barton, J., and O'Flynn, B. 2017. "A Review of Activity Trackers for Senior Citizens: Research Perspectives, Commercial Landscape and the Role of the Insurance Industry," *Sensors* (17:6), pp. 1-39.

Thomson, S., Figueras, J., Evetovits, T., Jowett, M., Mladovsky, P., Maresso, A., Cylus, J., Karanikolos, M., and Kluge, H. 2014. "Economic Crisis, Health Systems and Health in Europe: Impact and Implications for Policy," 2077-1584, WHO Regional Office for Europe, Copenhagen, Denmark.

Uschold, P., Potthoff, P., and Güther, B. 2005. "The New Private Health Insurance Subscribers," *Gesundheitswesen* (67:8-9), pp. 594-604.

Van der Heijden, H. 2004. "User Acceptance of Hedonic Information Systems," *MIS Quarterly* (28:4), pp. 695-704.

Veale, M. 2018. "Data Management and Use: Case Studies of Technologies and Governance" Retrieved on April 30, 2020 from https://osf.io/preprints/socarxiv/rwgs9/

Venkatesh, V., Morris, M. G., Davis, G. B., and Davis, F. D. 2003. "User Acceptance of Information Technology: Toward a Unified View," *MIS Quarterly* (27:3), pp. 425-478.

Visana. 2020. "My Points" Retrieved on April 30, 2020 from https://www.visana.ch/fr/visana/medias_publications/medias/communiques/2019/2019-09-02

Von Entreß-Fürsteneck, M., Buchwald, A., and Urbach, N. 2019. "Will I or Will I Not? Explaining the Willingness to Disclose Personal Self-Tracking Data to a Health Insurance Company," in *Proceedings of the 52nd Hawaii International Conference on System Sciences*, Honolulu, USA, pp. 1351-1361.

West, P., Giordano, R., Van Kleek, M., and Shadbolt, N. 2016. "The Quantified Patient in the Doctor's Office: Challenges & Opportunities," in *Proceedings of the 2016 Conference on Human Factors in Computing Systems*, San José, USA, pp. 3066-3078.

Whitson, J. R. 2013. "Gaming the Quantified Self," *Surveillance & Society* (11:1/2), pp. 163-176.

Whooley, M., Ploderer, B., and Gray, K. 2014. "On the Integration of Self-Tracking Data Amongst Quantified Self Members," in *Proceedings of the 28th International British Computer Society - Human Computer Interaction Conference* Southport, UK, pp. 151-160.

Wilson, H. J. 2013. "Wearables in the Workplace," *Harvard Business Review* (91:11), pp. 23-27.