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SELECTED ESSAYS ON HEALTH DECISIONS AND PERSONALIZED MEDICINE

Kalouguina Veronika

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FACULTÉ DES HAUTES ÉTUDES COMMERCIALES

DÉPARTEMENT DE SCIENCES ACTUARIELLES

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THÈSE DE DOCTORAT

présentée à la

Faculté des Hautes Études Commerciales
de l'Université de Lausanne

pour l'obtention du grade de
Docteure en Sciences actuarielles

par

Veronika KALOUGUINA

Directeur de thèse
Prof. Joël Wagner

Co-directeur de thèse
Prof. Christophe Courbage

Jury

Prof. Christian Zehnder, président
Prof. Séverine Arnold, experte interne
Prof. Stéphane Loisel, expert interne

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I M P R I M A T U R

Sans se prononcer sur les opinions de l'autrice, la Faculté des Hautes Etudes Commerciales de l'Université de Lausanne autorise l'impression de la thèse de Madame Veronika KALOUGUINA, titulaire d'un bachelor en Sciences économiques de l'Université de Genève et d'un master en Sciences économiques de l'Université de Genève, en vue de l'obtention du grade de docteure en Sciences actuarielles.

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November 2022

Veronika Kalouguina

This thesis is composed of five essays analyzing health decisions under the light of personalized medicine (PM). The first paper addresses the subject of portfolios of health-preventive activities. Using American survey data, we empirically demonstrate the importance of the personal doctor as well as of information-related variables in the size of the portfolio of preventive activities. Another aim of this paper is to understand the dynamic between different health preventive decisions in the formation of a health-preventive activities portfolio. In the second essay, we integrate health insurance in the decision scheme. We aim to understand how lifestyle choices are correlated with health insurance decisions in Switzerland, defined by the selection of a plan and a level of deductible. Our empirical analysis uses Structural Equation Modeling and documents the relationship between lifestyle health decisions, health care services consumption and health insurance features selection. The following essays dive deeper into the concept of PM and its integration in the Swiss health care system. The third paper shifts the focus from the individual to the payer of PM technologies, such as the health insurer or the government. In this paper, we performed a literature review on the subject of PM and its financing. After careful selection of the related research, we extract a body of 52 relevant publications in which we highlight three recurrent challenges: economic relevance of PM, governance challenges and healthcare system implementation. We are also able to identify solutions proposed to those challenges, along with examples of successful integration of PM in health care systems. The last three chapters make use of a survey conducted for the purpose of this research. This survey allows a two-dimensional analysis via the use of framings (i.e. division of the sample with the display of two different informations). In the fifth chapter the survey data conducted on 1 000 individuals residing in Switzerland, we concentrate on the effect of the payer of PM technologies on the willingness to undergo a genetic test. We are able to empirically document the impact of the nature of the payer on the willingness to undergo a genetic test. Additionally, we unveil the creation of a collaborative relationship between the individual and the health insurer when the latter is the payer of the genetic test. Finally, the last essay of this thesis makes use of another framing the in survey, shedding light on individuals' preferences on the nature of the storage of the data collected through apps or wearable medical devices and their readiness to use these PM technologies.

Résumé de la thèse

Cette thèse est composée de cinq essais analysant les décisions de santé sous le prisme de la médecine personnalisée (MP). Le premier article aborde le sujet des portefeuilles d'activités préventives. Dans ce chapitre, nous démontrons empiriquement, en utilisant les données d'un sondage américain, l'importance du médecin de famille ainsi que des variables liées à l'information dans la taille du portefeuille d'activités préventives de la santé. Un autre objectif de cet article est de comprendre la dynamique entre les différentes décisions de prévention en matière de santé dans la formation d'un portefeuille d'activités préventives. Dans le deuxième essai, nous intégrons l'assurance maladie dans le schéma de décision. Nous cherchons à comprendre comment les choix de style de vie sont corrélés aux décisions d'assurance maladie en Suisse, définies par la police et le niveau de franchise. Notre analyse empirique utilise un Modèle d'Equations Structurelles afin de documenter la relation entre les décisions de santé liées au mode de vie, la consommation de services de soins de santé et le choix des caractéristiques de l'assurance maladie. Les essais suivants approfondissent le concept de MP et son intégration dans le système de santé suisse. Le troisième article part du point de vue du payeur des technologies de la MP, tel que l'assureur maladie ou le gouvernement afin de faciliter leur intégration dans le système actuel. Dans cet article, nous effectuons une revue de la littérature concernant la MP et son financement. Après une sélection minutieuse des articles scientifiques, nous avons extrait un corpus de 52 publications pertinentes dans lequel nous mettons en évidence trois défis récurrents : la pertinence économique de la MP, les défis de la gouvernance et la mise en œuvre dans système de santé. Nous avons également identifié les solutions proposées pour relever ces défis ainsi que des exemples d'intégration réussie de la MP dans les systèmes de soins de santé. Les deux prochains et derniers chapitres s'appuient sur un sondage menée dans le cadre de cette recherche. Ce sondage permet une analyse bidimensionnelle grâce à l'utilisation de "conditionnement" (i.e. division de l'échantillon avec présentation de deux informations différentes). Avec les données de cette enquête menée auprès de 1 000 individus résidant en Suisse, nous nous concentrons, dans le cinquième chapitre, sur l'effet du payeur des technologies PM sur la volonté des individus à réaliser un test génétique. Nous documentons empiriquement l'impact de la nature du payeur sur la volonté de réaliser cedit test. De plus, nous dévoilons la naissance d'une relation de collaboration entre l'individu et l'assureur maladie lorsque ce dernier est le payeur du test génétique. Enfin, le dernier papier de cette thèse utilise un autre "conditionnement" dans le sondage, afin de mettre en lumière les préférences des individus sur la nature du stockage des données collectées par le biais d'applications ou de dispositifs médicaux portables et leur disposition à utiliser/continuer d'utiliser ces technologies de MP.

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Chapter 1

Introduction

This first chapter sets the framework of research of this thesis, laying the ground for a common understanding of the notion of health risks management as well as the functioning of the health care system in Switzerland. A definition and introduction to Personalised Medicine allows the reader to fully grasp the concept before diving into a brief summary of the thesis and thoughts for future research.

1.1 Health risks management

Individuals face several risks every day. One risk, however, is more important than the others, as it touches the very ability to go on in life: the health risk. Mindfully or not, each lifestyle choice leads to an increase or a decrease of the probability of developing certain health conditions.There are several ways to prevent a health condition from happening or to alleviate its consequences, should it have happened. Such measures are for instance a healthy diet (Block et al., 1992, Steinmetz and Potter, 1996), exercising (Warburton et al., 2006), regular health screenings or the choice of a tailored medication. Hence, individuals have access to several strategies that they can undertake to preserve their health, such as focusing on good health behaviors, regular health checks or a combination of health preserving actions. That hypothesis in mind, Venturelli et al. (2019) find that individuals who display "bad" health behaviors do tend to perform health preventive activities than those who display healthy practices. Another study by Carlos et al. (2005) demonstrates that men who underwent a prostate cancer screening were more likely to also undergo a screening for colon cancer, thus confirming the presence of health preventive strategies. Understanding this decision-making behavior regarding what portfolio of preventative activities people choose and what factors influence their decisions lies the ground for relevant policymaking. Indeed, governments and insurers can gain from such knowledge, as they will be able to more efficiently promote good health behaviors among citizens and insureds.

A common way to reduce the consequences of a health condition is insurance. In Switzerland,

basic health insurance is mandatory for all residents and covers basic health risks. However, it does not cover all types of medicine (e.g. alternative medicine), dental treatments or prescription glasses purchases for instance. For these risks, if the individual wants to seek financial protection, it is possible to subscribe to a complementary health insurance policy, which coverage goes beyond the basic one. Regarding the compulsory health insurance policy, the premiums solely depend on the age (0–18, 19–25 and 25+ years old groups) and the region of residency and the reimbursement policies are set by the Federal Law. To fine tune their choice for the basic coverage, residents of Switzerland have two features to chose from: the insurance plan and the level of deductible.

Insurance plans There are four categories of health insurance plans. The "standard" plan is chosen by the majority of policyholders. Under this plan, the insured is completely free to chose to visit any doctor or specialist. This plan comes with the highest premiums. The three alternative plans include restrictions, either in the set of doctors you can visit, pharmacies you can get your prescriptions from or having to call a medical center before making a doctor's appointment. These plans display lower premiums by 15 to 20% than the standard plan.

Deductible levels This feature is applied yearly in all insurance plans and describes the costs the insured pays out-of-pocket before any reimbursement mechanism takes place. Policyholders can choose from six levels of deductible, i.e., CHF 300, 500, 1 000, 1 500, 2 000 and 2 500. Once the level is reached, there remains a yearly co-payment of 10% up to CHF 700 on the additional costs.

1.2 What is personalized medicine?

In addition to a deeper understanding of the whereabouts of health risks prevention and mitigation, it is crucial to anchor them into the actual context. The rapid health technologies expansion and a decrease in its costs allows a broader population to have access to their personal health data such as sleep, heart rate, exercise, blood pressure, blood glucose or feminine health recording to name a few. Dunn et al. (2018) have performed an assessment of tracking devices called "wearables" and believe they are causing a medical revolution. In addition to the increased use and easiness to collect health data, in April 2003, the Human Genome Project declared to have completed the sequencing of the human genome. Despite this considerable advance in medical technology and the prospects it has brought, in October 2003, the price of sequencing a genome was above 40 million dollars, rendering this technique far too expensive for regular clinical use. Fortunately, as displayed in Figure 1.1[1], these costs have decreased at a rather fast pace, falling durably below USD 1 000 since February 2019 and being at the affordable level of USD 562 in August 2021. With accessible prices, genetic sequencing allows

[1]Source: `www.genome.gov/sequencingcostsdata`

practitioners to better understand the risks an individual bears in his/her genome to develop a certain health condition (Kurian et al., 2014; Lin et al., 2016). Using this information, the medical team can advocate a lifestyle change to accordingly reduce the probability of occurrence of a disease presenting a high risk. In their literature review of lifestyle changes aided by genetic sequencing, Horne et al. (2018) found that, when combined with concrete actionable adjustments, provision of genetic testing can lead to encouraging behavioral changes, especially in nutrition. These findings have recently been confirmed by an Italian study of 152 individuals who indeed proceeded to lifestyle changes following the results of genetic testing (Oliveri et al., 2022). Furthermore, genetic testing can be of high value in the process of exploration for the most adequate treatment for each individual. When the current approach is often called "trial-to-error" or "one-size fits all", sequencing the genome of a cancerous cell can, for example, facilitate the choice of the most efficient treatment for this particular mutation. For instance, in the case of breast cancer, patients who present a clear genetic signature of a cancer-inducing genetic mutation have been shown to be more responsive to certain treatments (Sotiriou and Pusztai, 2009), and being administered the incorrect mutation-wise treatment is very costly for the patient in terms of side effects (Spear et al., 2001; Sultana et al., 2013) and time lost in combating the disease, as well as the financial burden for the sponsor. In that sense, genomics have enabled a deeper understanding of health risks at the individual level to provide a tailored and personalized health care (Liefers and Tollenaar, 2002).

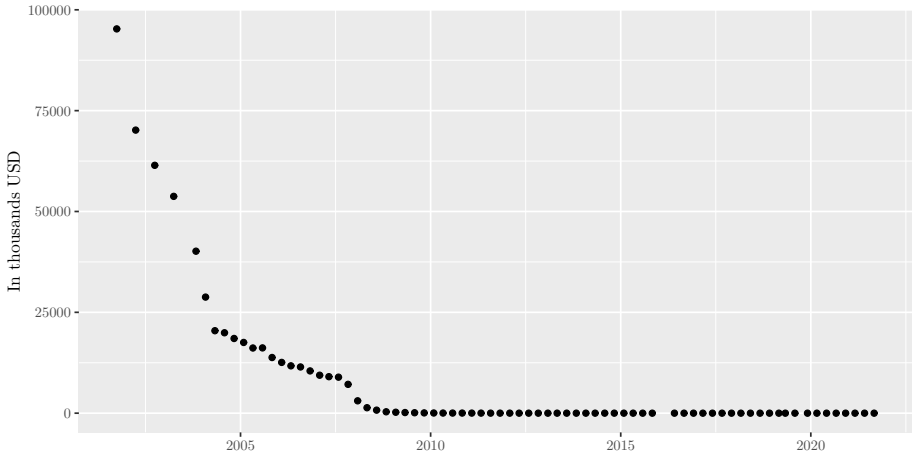

Figure 1.1: Evolution of the costs of genome sequencing

A medicine including these new techniques, has hence all the means to be more personalized and is rightfully called Personalized Medicine (PM), stratified medicine, precision medicine or P4 (predictive, preventative, personalized, participatory) medicine. Although, there is no consensus in the literature regarding one single definition of PM (see Redekop and Mladsi, 2013; Schleidgen et al., 2013), the idea is rather simple to grasp. PM is the usage of health data (biological and genetic) to allow a genetics-guided prevention of risks and tailored treatment, which is projected to spare the patients' and healthcare system's resources and efforts. This new paradigm is rooted in the usage of data to allow an optimization of resources. It is therefore enabled by the systematic collection of the individual's lifestyle, metabolic and genetic data to form a health cloud. To this aim, since April 2017, Switzerland requires hospitals to adopt electronic health

records (EHR) to allow instant access to the patient's clinical data and foster data sharing among the medical team, hence also increasing efficiency. The patient has a complete control over the access to the EHR with every connection being recorded and traceable (De Pietro and Francetic, 2018). Nevertheless, despite all the efforts to facilitate the implementation of PM into clinical reality, issues about privacy and ethics do arise when dealing with sensitive data. Indeed, in practice, the implementation of PM tends to be more complicated, as several questions come to mind regarding its implementation into the established healthcare system. The first grand question concerns the inclusion into the financing of personalized prevention and therapies. One key challenge lies in the mismatch between the high costs but long-term payoffs of PM. The inclusion of PM into everyday life largely depends on health insurers, that are key players of the healthcare ecosystem. They face, however, costs that are higher than those of traditional medicine, especially when dealing with specific genetic diseases or orphan drugs, the cost of developing a new treatment is only dispersed on a smaller population, rendering very high prices for specific drugs. Another question to be asked, without diving into ethics and societal changes involved by the advent of PM that are out of the scope of this research, is how this data should be used and stored. What are individuals preferences regarding the sharing of their personal health data and how the storage affects their willingness to use these novel technologies. These are among the topics this thesis discusses.

1.3 Structure of the thesis

After the introduction in this chapter, in the second chapter of this thesis, we address the subject of portfolios of preventive activities. By using the American Behavioral Risk Factor Surveillance System dataset from 2016, we aim to understand how people construct their preventive strategies, i.e., what factors influence their choices and how these preventive actions interact with each other. From the 22 510 observations in the Behavioral Risk Factor Surveillance System dataset, we find that information-related variables play the strongest role in the decision to perform a medical screening or vaccination. That is, individuals who are or have been a caretaker or individuals who have an easy access to health information tend to have a larger portfolio of health preventive activities. In this chapter we also highlighted the importance of the personal doctor in the number of health screenings performed, suggesting that medical personnel is the best channel for a health prevention-related policy planning to increase the number of health checks to protect the population from the consequences of a late detected health condition. Another interesting result stemming from this chapter hints that performing a preventive activity leads to the performance of another. More precisely, our regression results suggest that if an individual underwent a health screening during the past 12 months, he/she is more likely to also get a vaccination during the same time period and vice-versa.

After bringing light to how individuals shape their health preventive strategies and their lifestyle, we want to integrate health insurance in the decision scheme. In the third chapter of this thesis, we aim to understand how the lifestyle affects individuals' choice for each basic Swiss health

insurance feature (also see Section 1.1), the plan and the deductible. Our empirical analysis, is based on the Swiss Health Survey data from 2017 including 9 301 observations. We make use of Structural Equation Modeling for the regression analysis, which allows us to express "latent" variables, health and health care services consumption through the use of "manifest" (observable) variables such as self-reported health, health conditions or the number of doctor visits for instance, while accounting for other lifestyle and socioeconomic variable such as age, income, diet or exercising as exogenous. The results fill the gap in the extant literature, as they provide empirical evidence for four conjectures. Firstly, we demonstrate that a "healthy" lifestyle defined by a low Body Mass Index, a diet with lots of vegetables and fruits, exercising and biking or walking for commuting is indeed associated with a better health. Subsequently, employing these results, we are able to document that health is the most significant driver of health care services consumption. For our third and fourth results concerning health insurance choice, we find that being a woman leads to opting for a lower level of deductible, whereas the higher the education, the higher level of deductible chosen. Education, seems to also influence the plan option, as a higher education level is associated with a higher propensity to prefer restricting and cheaper plans. Finally, expectedly, a higher income comes along with a lower deductible level. Our last results allow us to bind all the precedent together to unveil the big picture of the factors coming into play for the choice of health insurance features. We lastly demonstrate that a low level of deductible coupled with an alternative insurance plan, signals a low health care services consumption. Aligning our results, making use of regression techniques, we prove that healthy behaviours correlate with a low health care services consumption, which in turn impact the choice of health insurance towards an alternative (more restrictive) plan and a high level of deductible.

Our fourth chapter shifts the focus from the individuals to the payer of PM. As outlined in Section 1.2, scientific progress is already allowing for a novel data and technology-based medicine. The challenge now arises for its implementation into the actual healthcare system. To be able to accurately judge the current state of PM in practice, the hurdles that it faces and the possible solutions, we perform a literature review. Our scanning of the literature is composed of 419 identified records on the thematic of PM and its financing, from which, after careful selection, backward and forward tracking we extract a body of 52 relevant publications. Throughout the scanning of the literature, we noticed that all the papers deal with at least one of the following subjects that we capture: economic relevance of PM, governance challenges and healthcare system implementation. Regarding economic relevance, there is too little evidence of the economic efficiency of PM and when there is, the metrics used differ between studies, rendering the comparison as well as meta-analysis very difficult. This is the first and probably the highest hurdle for the coverage of PM by payers. Indeed, a lack of data assessing its economic value demands the payer to blindly reimburse the often high costs of the precision techniques. To be able to make such a decision, a rational economic agent hence requires data, which the field cannot yet provide. Fortunately, based on the literature and existing solutions to the issue, we present ways in which this evidence can be generated. Among them, we could note manufacturer-payer partnership to counter the lack of data, combined with the establishment of universal guidelines

and units of valuation to enable comparison. The second obstacle, i.e., the governance question, resides mostly in the discrepancies among the existing contracts and reimbursement thresholds. To tackle the issue, the creation of a centralized Health Technology Assessment body is often cited in the literature, to unify reimbursement thresholds and allow for a clearer communication as well as a sharing of information between stakeholders. Concerning the implementation of PM in the healthcare system, the hardship lies in the high costs and the related difficulty to predict expenses for the payer. Multiple solutions have been excerpted from the review with several examples of countries with successful implementation of PM technologies and payer-manufacturer partnerships such as a price-volume or risk-sharing agreements. Overall, the advent of PM raises a discussion on the nature of public health. The literature suggests moving to a value-based pricing and coverage of PM technologies, thus shifting the understanding of health as an investment rather than a cost.

The fifth chapter presents the survey conducted for the purpose of this research, along with the descriptive statistics of key information variables on the topic of PM. The survey, conducted in March 2020 by a professional polling agency addressed the topic of PM with a focus on genetic testing conducted in a preventive setting, i.e., to extract disease risk information to plan the frequency of health checks and improve lifestyle to decrease the risk or postpone the occurrence of a disease. Respondents are residents in Switzerland, evenly distributed among gender and age from 25 to 65 years. The first two variables going under the lens deal with the reason for acceptance or refusal to use health-related apps or wearable devices and blood or genetic tests. The biggest driver explaining willingness to use these technologies was prevention for up to 50.6% of the surveyed population for apps and wearables and 62.4% for blood or genetic tests. Curiosity followed as a motivation to use app or wearables for 57.3% of the sample, and was even a greater driver for blood or genetic tests (60%). The major reason of reluctance to use health-related apps and wearable devices is concern with data protection for 57.4% of those who refuse to use these technologies. For blood and genetic tests, this is also an obstacle for 52.5% of individuals who are not using and will not use these tests. Another question of our survey presented several actors with which the individual can share their anonymized data from apps, wearables as well as blood and genetic tests from which we obtained the same ranking. The actor trusted the most with this sensitive data is the doctor, with up to 80% of agreement for blood and genetic test information. At the second place are family and friends, closely followed by university researchers (45.3% for apps and 40% for blood and genetic tests). The fourth actor is the insurer, with whom 31.4% of the sample agreed to share anonymized app and wearables information and 23.6% to share anonymized information from blood and genetic tests. The remaining analysis focuses on genetic tests in the preventive medicine context. The survey maps individuals' incentives and barriers to undergo a genetic test, along with the general public sentiment towards the usage of genetic testing in society. Overall, the sentiment is rather positive, with health considerations being the strongest motive (having the information about one's hereditary diseases and cancer risks is an incentive for 63% of the sample). Cost, on the other hand, is a discernible concern, with the fear that the price of testing may be too high for 55.5% of the survey people. The fear of possible segregation or discrimination between "good"

and "bad genomes" is present but not dominant as it is a concern for less than a fourth of the population under study. Finally, for insurance-related considerations, 36.6% of the sample believe it will be more difficult for members of their family to underwrite an insurance contract where 33.1% disagree with the statement. Lastly, 42.6% of the inquired population think that in the future, insurance companies will ask for DNA sequencing to establish a premium, with which thought 33.7% disagree.

In chapter 6, we make further use of the data collected in the survey presented in the previous chapter. The ad-hoc survey allows a two-dimensional analysis of the data, fulfilling two aims. Firstly, through regression results along five set of possible factors, we provide evidence on the drivers of willingness to undergo a genetic test and share the anonymized related results. Among socioeconomic, lifestyle, insurance, political and sentiment factors, we find that insurance and sentiment factors play a strong role in the decision-making of genetic testing and data sharing willingness. For instance, using the health insurer's smartphone app leads to an increase of 16.5% in the willingness to undergo a genetic test and of 27.6% to share the anonymized related data with the health insurer. Additionally, we highlight that individuals owning a complementary health insurance policy are less likely to share anonymized test results with their insurer. To test the robustness of our results, we use a random forest approach on the total regression model to get an importance ranking of the effects and find similar results along both methods. The second dimension of our analysis introduces the payer with a division of the sample. Indeed, in a second step, we divide our sample into two subsamples of equal size and frame the questions with either the health insurer or the individual itself as a payer for the genetic testing. By doing so, we seize the effect of the health insurer as a payer and demonstrate that there is an increase of 24.8% of willingness to undergo a genetic testing compared to the framing when the individual alone bears the costs. It is subsequently notable that the subsample framed with the insurer as a payer is 9.4% more likely to share the anonymized results of a genetic sequencing with the health insurer.

The last chapter employs data from the survey, targeting individuals' preferences on the nature of the storage of data collected through apps/wearables and blood or genetic tests. Precisely, for half of the sample, it was stated that the data should be used as a common good and shared to increase knowledge on public health, while the other half was told that the data is to be kept in a personal safe and with individualized access. These framings yielded information regarding the willingness to use apps/wearables or blood and genetic tests according to the storage discrepancies. Additionally, aside from controlling for socioeconomic variables, regressions also take into account opinions about the role of the state in the provision of social security or the regulation of data storage, for instance. The results of these regressions suggest that there is no strong correlation between socioeconomic factors and the willingness to collect data through either health technology. The belief that it is the role of the state to store and use data, however, is significantly positively correlated with potential usage of both apps or wearables and blood or genetic tests with an increase of around 18% in willingness. Finally, our most important result concerns the framing stating that the collected data should be privately stored, with usage and

sharing possible only with the consent of the individual. For the surveyed population which received this framing, there is an increase in willingness/continuation to use health-related apps or wearable devices of 23.7%. Even though, the increase is not as considerable as when the question about willingness/continuation to use blood or genetic tests is asked, the effect is still significant and quite strong with a 13.7% increase. This disparity can be explained by the sensitive nature of blood or genetic data, rendering individuals less likely to be willing to share it, disregarding the type of storage. Our study hence offers insights on individuals' preferences regarding the storage and access to their health-data – data that is at the heart of PM technologies. This knowledge is paramount for policymakers to establish a framework which allows the optimal collection of data.

1.4 Where are we now?

Access to a constant stream of health data gave rise to the PM paradigm, however, it is easier to extract relevant insights from this data than changing a whole system to use them at their value. The scientific knowledge and technologies are expanding the frontiers of health understanding. The hurdles for the implementation of PM into clinical use are now more likely to come from other areas. Indeed, a lot still needs to be defined to provide homogenous quality evidence to measure the cost-efficiency of the technology to be covered by the payers. Among the solutions, standardization of health technology assessments as well as reimbursement criteria need to be well-defined. Subsequently, contracts between manufacturers and payers of these technologies will permit the production of the missing data. Finally, from the payers' side, the measurement of the value created by PM technologies needs to be revised, as there is a mismatch between the high costs in the short term and the payoff in the long term. The payers are hence the final link of the chain to grant the integration of PM in health care system.

From a consumer perspective, to provide PM legitimacy there is literacy to build the required expertise to which this thesis is contributing. On the political front, establishing guidelines for the collection and storage of sensitive data is crucial to build a safe environment for the consumer, and only then, allow the expansion of usage of PM technologies. A study by Gröninger and Lacher (2017), highlighted the data protection concerns. Among 224 survey individuals, 23% admitted that data protection concerns are one of the principal reasons to reject collection of health data. On this topic, our research goes a little further and proves that the majority of individuals wants to stay in control of their data. Privacy and the storage of data of such nature is another topic which merits further investigation to lay the ground for a successful integration of PM into everyday lives.

Additionally, the results we obtain are valid for Switzerland or countries under the same health care system. Extending this research to other models of health care would further increase the knowledge on health decisions. From the health insurance standpoint, it would be valuable to investigate more pragmatic questions, such as the amount of reduction in the premium for

which individuals would be willing to share their health data collected through wearable devices. Another interesting topic to investigate is the nature of the insurance for PM technologies, i.e., whether there be should a health insurance for specific PM therapies at a national level or specific health insurance offering coverage. To answer these questions, it may be insightful to have a look at other countries such as Estonia or Finland who are quite advanced in the implementation of PM into the health care system. For instance, Estonia started the inclusion of PM by laying the legal framework to govern genomic research in the population through the Human Genes Research Act that is in force since 2001.[2] The population itself, is also very positive regarding the existence of the national Estonian Biobank. For instance, in 2019, 75% of surveyed individuals supported the biobank (Leitsalu, 2016) hence, giving legitimacy to the clinical integration and daily use of PM. Finland, as another example, has also made of the integration of PM a national goal. A strong nationwide network of eight biobanks allows the collection, storage and analysis of the population's health data. However, the creation of data to assess the cost-efficiency of PM technologies is still work in progress.

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Chapter 2

On Portfolios of Preventive Decisions for Multiple Health Risks – Evidence from US-Based Data

Abstract: Individuals face multiple health risks and therefore can undertake many preventive activities simultaneously, thus creating a portfolio of preventive activities. In this article, we first investigate the determinants likely to influence the composition of portfolios of preventive activities. Second, we look at the interactions between preventive activities. We use the US Behavioral Risk Factor Surveillance System survey data set conducted in 2016, comprising 22 510 observations from 50 states and US territories. Our results show that information-related variables, in particular, being aware of illness, having access to information and having a personal doctor, increase the portfolio size of preventive activities. We also show that vaccinations tend to be performed together with screening activities and to a lower extent with exercising.

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2.1 Introduction

Given that individuals face multiple risks, for example, risks of cancers, influenza, flu and heart attacks, they are most likely to undertake different preventive activities simultaneously, for example, cancer screenings, vaccination, health checkup and regular physical activity (Spring et al., 2012). Hence, they, create a portfolio of preventive activities. Understanding the drivers of such portfolios of preventive activities is crucial to design efficient health policies. Indeed, public authorities must be able to foresee the potential outcome of a policy and to predict the spillover effects of a prevention-oriented policy before implementing it, especially when another program is already targeting a different prevention type.

The importance of information in driving specific preventive activities has already been highlighted in existing literature, including awareness of health issues (Slark and Sharma, 2014), health literacy (see e.g., DeWalt et al., 2004; Fernandez et al., 2016), health knowledge (Vanslyke et al., 2008) and the role of the general practitioner as a means and source of health information (Qi et al., 2006; McIlfatrick et al., 2013). Along with information, other determinants of specific preventive activities include socioeconomic factors, such as age, marital status, the level of income and self-reported health (Welch et al., 2008; Dorner et al., 2013), as well as risk attitudes (Hoebel et al., 2014) and health insurance (Simon et al., 2017). However, most of this literature addresses the determinants of one specific preventive activity instead of a whole portfolio of individual preventive decisions. We thus aim to fill this gap in the literature by specifically considering in this article, the drivers of the number of preventive activities, that is, of the size of portfolios of preventive activities. We especially focus on health-related information drivers, including experience with health risks as related to being a caregiver, having easy access to health information and having a general practitioner.

The determinants of one preventive activity can also affect the realization of another, giving rise to the issue of complementarity between preventive activities (Beydoun and Beydoun, 2008). For instance, Carlos et al. (2005b) showed that prostate-specific antigen (PSA) screenings are more likely to be performed with a colorectal cancer screening. Welch et al. (2008) documented that regular physical exercise and being a nonsmoker are determinants of feminine cancer screening. However, considering statin use and health behaviors as preventive activities, Kaestner et al. (2014) found conflicting evidence for the hypothesis that investments in disease prevention are complementary. The question of complementarity hence remains open. We hypothesize that the relationship between preventive activities might depend on their nature, for example, being behavioral or medicalized.

In this article, using the US Behavioral Risk Factor Surveillance System (BRFSS) survey data set, which encompasses many types of preventive activities, we aim at (1) investigating the determinants likely to alter the composition of portfolios of preventive activities, with a focus on the role played by health-related information, and (2) identifying preventive activities that are complementary to each other and encourage each other's uptake.

2.2 Methodology

2.2.1 Data

For the purpose of our study, we used the BRFSS survey data set. BRFSS is a health-related phone survey, which is carried out in all the 50 states of the US with the District of Columbia and three US territories. The BRFSS collects state data about US residents regarding their health-related risk behaviors, chronic health conditions and use of preventive services. The BRFSS data set was particularly well suited for our analysis, as it contains information on several types of preventive activities, including both medical and nonmedical preventive activities, including mammography, Papanicolaou (Pap) test, human papillomavirus (HPV) test, blood stool test for colorectal cancer, colonoscopy, PSA test, checkup, tetanus and flu vaccinations and exercising. We used the 33$^{\text{rd}}$ wave conducted in 2016, which is composed of 22 510 complete observations.

2.2.2 Variables

Dependent variables

We used two types of dependent variables for preventive activities classified by gender. We subdivided the population into two groups, individuals below and above 50 years, following the U.S. Preventive Services Task Force recommendations regarding cancer screenings (Grossman et al., 2018). This allows for a better tailored portfolio, as several cancer screenings are not available or are very rarely administered below the age of 50.

The first dependent variable was the sum of preventive activities per individual performed during the past 12 months. These preventive activities are presented in Table 2.1. The number of performed preventive activities summed up to a maximum of six for women below 50 years and up to a maximum of nine for women above 50 years. As for men, this number went up to four for men below 50 years and seven for those above 50 years.

Before 50 y.o.			**After 50 y.o.**		
Behavioral	Screenings	Vaccination	Behavioral	Screenings	Vaccination
Exercise ♀/♂	Check up ♀/♂ HPV test ♀ Pap test ♀	Flu vac. ♀/♂ Tetanus vac. ♀/♂	Exercise ♀/♂	Blood stool ♀/♂ Colonoscopy ♀/♂ Check up ♀/♂ HPV test ♀ Pap test ♀ Mammography ♀ PSA test ♂	Flu vac. ♀/♂ Tetanus vac. ♀/♂

Table 2.1: Portfolios of preventive activities by types

The second type of dependent variable was a selection of preventive activities, which were segregated in three types according to their nature, that is, behavioral preventive activity, screening

and vaccinations, as presented in Table 1. The classification of preventive activities by types allowed us to investigate the interactions between preventive activities of different natures. The underlying hypothesis was that relationships between preventive activities may depend on the type of prevention, and the former may change depending on the individual's age.

Information-related variables

We defined three variables to account for the role of health-related information on preventive activities. The first variable was a caregiver dummy variable. The underlying assumption justifying the use of this variable was that caregivers have a greater experience with health risks and their consequences, which may in turn incentivize them to pay more attention to their own health (Banford et al., 2001; Broughton et al., 2011). This variable hence proxied the effect of awareness about potential health issues and their consequences.

The second variable was a dummy variable assessing the ease with which the respondent gets advice or information about health or medical topics if needed. This variable allowed to control for the accessibility of information to the individual, which in turn may influence preventive decisions.

The third variable was a personal doctor (PD) dummy depending on whether the individual reported having one person he/she thinks of as a PD or healthcare provider or not. Having a PD is a well-recognized source of health information, and individuals reporting having a PD should be more likely to have better and more personalized information about the benefits of preventive activities (Noar et al., 2007).

Other variables

Following the literature, we included a set of control variables that have been shown to affect preventive decisions. We first included a series of socioeconomic factors, namely, age, marital status, number of children below 18 years, education higher than high school, preferred race, employment and income. Concerning health-related control variables, we included health coverage, which is a dummy variable assessing whether the respondent has any kind of health coverage, including health insurance, prepaid plans such as health maintenance organizations (HMOs) or government plans such as Medicare or Indian Health Service. We also included the subjective health, which was a count variable ranging from 1 (poor) to 5 (excellent). Finally, we added a health-risk tolerance variable to capture the idiosyncratic relationship of the respondent to health risks. This variable was a dummy controlling for whether the respondent smoked in his/her entire life at least 100 cigarettes, has driven drunk at least once in the past 30 days or has had a red or painful sunburn that lasted a day or more during the past 12 months.

2.2.3 Descriptive statistics

Table 2.2 provides a concise description of the set of variables used in the next section's econometric specifications.

Variable	Mean	Std. Dev.	Min.	Max.	N
Dependent variables					
Nb. of preventive activities ♀< 50 y.o.	2.424	1.941	0	6	4 373
Nb. of preventive activities ♀> 50 y.o.	2.561	2.362	0	9	7 868
Nb. of preventive activities ♂< 50 y.o.	2.165	1.198	0	4	3 719
Nb. of preventive activities ♂> 50 y.o.	2.367	1.939	0	7	5 877
Screenings ♀< 50 y.o.	1.288	1.156	0	3	4 373
Screenings ♀> 50 y.o.	1.575	1.509	0	6	7 868
Screenings ♂< 50 y.o.	0.595	0.491	0	1	3 719
Screenings ♂> 50 y.o.	1.14	1.056	0	4	5 877
Vaccinations	1.044	0.746	0	2	19738
Flu vaccination < 50 y.o.	0.324	0.468	0	1	8 403
Flu vaccination > 50 y.o.	0.505	0.5	0	1	14 029
Mammography	0.514	0.5	0	1	12 508
Colonoscopy	0.189	0.391	0	1	5 703
Independent variables					
Caregiver	0.213	0.41	0	1	22 510
Info. access	0.752	0.432	0	1	22 510
Personal Doctor	0.820	0.384	0	1	22 510
Male	0.439	0.496	0	1	22 510
Age					
18 to 34	0.161	0.368	0	1	22 510
35 to 49	0.214	0.41	0	1	22 510
50 to 64	0.316	0.465	0	1	22 510
65 to 74	0.19	0.392	0	1	22 510
75+	0.119	0.324	0	1	22 510
Preferred race category					
White	0.623	0.485	0	1	22 510
Hispanic	0.219	0.414	0	1	22 510
Black	0.116	0.32	0	1	22 510
Asian	0.014	0.116	0	1	22 510
Married	0.524	0.499	0	1	22 510
Children	0.525	1.004	0	9	22 510
Education	0.697	0.46	0	1	22 510
Employment status					
Employed	0.45	0.498	0	1	22 510
Self-employed	0.088	0.284	0	1	22 510
Student	0.023	0.15	0	1	22 510
Retired	0.273	0.446	0	1	22 510
Out of work	0.135	0.342	0	1	22 510
Income level					
< 25 000 $	0.315	0.464	0	1	22 510
from 25 000 $ to 50 000 $	0.227	0.419	0	1	22 510
> 50 000 $	0.458	0.498	0	1	22 510
Healthcare coverage	0.948	0.222	0	1	22 510
Subjective health	3.451	1.072	1	5	22 510
Health risks tolerance	0.146	0.353	0	1	22 510

Table 2.2: Summary statistics

2.2.4 Econometric methodology

Following Carlos et al. (2005a) and Welch et al. (2008), who used the same BRFSS data set, our first regression was a linear model with White standard errors to correct for heteroskedasticity. The dependent variable was the number of individual preventive activities. The explanatory variables were the set of informational factors and all the individual control variables. This first model aimed at investigating the determinants of the size of preventive activities' portfolios.

We also considered a submodel for which the sum of preventive activities corresponded only to either screening activities or vaccination activities to address the determinants of more specific portfolios of preventive activities, that is, a portfolio of screening activities and a portfolio of vaccination activities.

The second linear regression, also corrected for heteroskedasticity with White standard errors, was run on the three groups of preventive activities described in Table 2.1. In addition to the information-related variables and our control variables, we included in the set of explanatory variables, the other preventive activities' groups. This second model aimed at investigating the interactions between different types of preventive activities.

2.3 Results and discussion

Results are presented in Table 2.3 for the overall portfolio of preventive activities, in Table 2.4 for the portfolio of screening activities and of vaccination activities, and in Table 2.5 and Table 2.6 for the interactions between different groups of preventive activities (respectively for women and men).

2.3.1 Information-related determinants

Starting with the caregiver variable, its effect on the size of the total portfolios of preventive activities is overall positive for individuals below the age of 50. For these individuals, having provided regular care or assistance to a person with health problems or disability during the past 30 days increases the size of the portfolio by 0.3 units for women and 0.24 for men.

As for the role of ease of access to medical information, it correlates positively and significantly with the size of the overall portfolio of preventive activities indifferent of age and gender. However, the ease of access to health information seems to be much higher for respondents of age 50 years and above. When it comes to the portfolio of screening activities, only women of age 50 years and above seem to be affected by the ease of access to information.

Regarding the variable PD, it positively and very significantly impacts the size of the overall portfolio of preventive activities disregarding age and gender. This variable is the most important driver of the size of the overall portfolio (β between 0.50 and 0.78). The presence of a PD is more valued by individuals of age 50 and above, as it represents for both men and women, one third to one half of the standard deviation of the size of the portfolio. The same results apply for portfolios of screenings and vaccinations.

Model	(1) # prev. ♀ < 50 y.o.	(2) # prev. ♀ > 50 y.o.	(3) # prev. ♂ < 50 y.o.	(4) # prev. ♂ > 50 y.o.
Info-related factors				
Caregiver	0.300***	−0.090	0.235***	0.058
	(0.104)	(0.099)	(0.089)	(0.106)
Info access	0.199*	0.399***	0.176**	0.229**
	(0.106)	(0.110)	(0.069)	(0.090)
Personal doctor	0.547***	0.727***	0.502***	0.779***
	(0.109)	(0.144)	(0.068)	(0.105)
Control variables				
Age (baseline: 18 to 34 y.o. / 50 to 64)				
35 to 49	−0.157		0.004	
	(0.101)		(0.067)	
65 to 74		−0.294**		0.110
		(0.119)		(0.112)
75+		−0.667***		−0.294**
		(0.136)		(0.139)
Preferred race category				
White	−0.101	0.433	0.045	0.097
	(0.295)	(0.312)	(0.179)	(0.240)
Hispanic	0.380	1.690***	0.166	0.308
	(0.356)	(0.407)	(0.211)	(0.364)
Black	0.066	0.883**	0.207	0.001
	(0.315)	(0.343)	(0.197)	(0.275)
Asian	−0.161	0.432	−0.418	−1.093***
	(0.355)	(0.528)	(0.284)	(0.381)
Married	0.014	−0.005	0.098	0.173*
	(0.109)	(0.099)	(0.070)	(0.096)
Children	−0.065*	−0.104	−0.003	0.001
	(0.035)	(0.087)	(0.027)	(0.065)
Education	0.182*	−0.010	0.184**	0.165*
	(0.101)	(0.100)	(0.073)	(0.094)
Employment status (baseline: Employed)				
Self-employed	−0.168	−0.351**	−0.107	−0.204
	(0.186)	(0.176)	(0.088)	(0.125)
Student	−0.096	−1.064**	0.340**	−0.628
	(0.188)	(0.470)	(0.135)	(0.950)
Retired	−1.308**	0.026	−0.633	−0.044
	(0.657)	(0.136)	(0.488)	(0.121)
Out of work	−0.128	−0.274*	0.182	−0.010
	(0.121)	(0.154)	(0.122)	(0.164)
Income level (baseline: < 25 000)				
from 25 000 $ to 50 000 $	−0.107	0.096	0.027	−0.116
	(0.136)	(0.135)	(0.096)	(0.128)
> 50 000 $	−0.023	0.084	0.216**	0.067
	(0.149)	(0.142)	(0.097)	(0.135)
Healthcare coverage	0.480***	0.326	0.119	0.336**
	(0.169)	(0.228)	(0.103)	(0.171)
Subjective health	−0.030	0.098**	0.051	0.125***
	(0.045)	(0.046)	(0.032)	(0.041)
Health risks tolerance	−0.090	−0.255*	−0.040	−0.089
	(0.123)	(0.133)	(0.079)	(0.119)
Control for state	Yes	Yes	Yes	Yes
N	4 373	7 868	3 719	5 877
R^2	0.059	0.046	0.141	0.056

Note: The significance levels are * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ and standard errors in parenthesis.

Table 2.3: Regression results for prevention portfolios

2.3.2 Socioeconomic determinants

Looking at the effect of some of our control variables, as shown in Table 4, being married has a positive impact on the overall portfolio of men above 50 years old. This is especially the case when it comes to the portfolio of screening activities. Looking at education, a level higher

Model	(5)	(6)	(7)	(8)	(9)
	Screen. ♀ < 50 y.o.	**Screen. ♀ > 50 y.o.**	**Screen. ♂ < 50 y.o.**	**Screen. ♂ > 50 y.o.**	**Vacc.**
Info-related factors					
Caregiver	−0.006	−0.020	0.065*	0.001	0.064***
	(0.028)	(0.020)	(0.034)	(0.027)	(0.021)
Info access	0.035	0.057***	0.044	0.038	0.075***
	(0.029)	(0.022)	(0.028)	(0.025)	(0.020)
Personal doctor	0.163***	0.167***	0.325***	0.229***	0.187***
	(0.029)	(0.034)	(0.027)	(0.033)	(0.023)
Control variables					
Age (baseline: 18 to 34 y.o. / 50 to 64)					
35 to 49	−0.036		0.020		
	(0.026)		(0.027)		
65 to 74		−0.029		0.043	0.091***
		(0.023)		(0.027)	(0.027)
75+		−0.071**		−0.060*	0.055*
		(0.028)		(0.034)	(0.033)
Preferred race category					
White	−0.113*	−0.007	−0.148**	−0.028	0.104*
	(0.067)	(0.075)	(0.075)	(0.064)	(0.054)
Hispanic	−0.037	0.255***	−0.079	0.015	0.221***
	(0.082)	(0.085)	(0.086)	(0.092)	(0.073)
Black	0.045	0.072	0.053	−0.017	−0.029
	(0.072)	(0.079)	(0.081)	(0.073)	(0.060)
Asian	−0.218**	0.072	−0.044	−0.089	−0.061
	(0.103)	(0.156)	(0.105)	(0.118)	(0.081)
Married	0.031	0.004	0.015	0.046*	−0.001
	(0.027)	(0.020)	(0.029)	(0.025)	(0.020)
Children	−0.013	−0.022	−0.011	0.001	−0.004
	(0.010)	(0.017)	(0.011)	(0.017)	(0.009)
Education	0.050*	−0.033*	0.017	0.020	0.096***
	(0.029)	(0.020)	(0.027)	(0.024)	(0.020)
Employment status (baseline: Employed)					
Self-employed	−0.104**	−0.051	−0.027	−0.044	−0.064**
	(0.047)	(0.041)	(0.038)	(0.034)	(0.028)
Student	0.005	−0.058	0.156***	−0.329**	0.128**
	(0.047)	(0.134)	(0.046)	(0.156)	(0.060)
Retired	−0.148	0.017	0.030	−0.026	0.052*
	(0.175)	(0.025)	(0.183)	(0.030)	(0.029)
Out of work	−0.028	−0.056*	0.234***	0.053	−0.003
	(0.033)	(0.029)	(0.046)	(0.041)	(0.028)
Income level (baseline: < 25 000)					
25 000 $ to 50 000 $	−0.043	−0.003	0.018	−0.023	−0.023
	(0.035)	(0.026)	(0.038)	(0.033)	(0.028)
> 50 000 $	−0.054	0.002	0.018	−0.001	0.058**
	(0.038)	(0.028)	(0.037)	(0.035)	(0.029)
Healthcare coverage	0.152***	0.092*	0.155***	0.158***	0.143***
	(0.046)	(0.056)	(0.041)	(0.056)	(0.034)
Subjective health	−0.020*	0.000	−0.011	0.010	−0.016*
	(0.012)	(0.009)	(0.012)	(0.010)	(0.009)
Health risks tolerance	−0.016	−0.022	−0.072**	−0.024	−0.067***
	(0.033)	(0.029)	(0.030)	(0.032)	(0.024)
Male					0.047***
					(0.018)
Control for state	Yes	Yes	Yes	Yes	Yes
N	4 373	7 868	3 719	5 877	19 738
R^2	0.073	0.036	0.205	0.060	0.160

Note: The significance levels are * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
and standard errors in parenthesis.

Table 2.4: Regression results for prevention portfolios by group-types

than a high school diploma leads to a larger overall portfolio in younger women and men of all ages. Healthcare coverage is also significant, mostly for portfolios of cancer screenings and vaccinations.

Model	(10) **OR Behav. < 50 y.o.**	(11) **OR Behav. > 50 y.o.**	(12) **Screen. < 50 y.o.**	(13) **Screen. > 50 y.o.**	(14) **Vacc. < 50 y.o.**	(15) **Vacc. > 50 y.o.**
Interactions						
Behavioral			−0.044	0.049	0.048	0.078**
			(0.066)	(0.067)	(0.043)	(0.031)
Screenings	0.848	0.948			0.103***	0.128***
	(0.119)	(0.089)			(0.037)	(0.028)
Vaccination	1.140	1.254**	0.111*	0.359***		
	(0.164)	(0.126)	(0.061)			
Control variables						
Caregiver	1.238	1.272**	0.012	−0.048	0.142***	0.005
	(0.199)	(0.135)	(0.066)	(0.064)	(0.043)	(0.031)
Info. access	1.064	1.012	0.050	0.193**	0.087**	0.110***
	(0.162)	(0.105)	(0.068)	(0.075)	(0.043)	(0.032)
Personal doctor	1.375**	1.114	0.357***	0.455***	0.080*	0.208***
	(0.220)	(0.198)	(0.067)	(0.099)	(0.043)	(0.044)
Age (baseline: 18 to 34 y.o. / 50 to 64)						
35 to 49	0.797		−0.115*		−0.024	
	(0.116)		(0.062)		(0.039)	
65 to 74		0.910		−0.284***		0.000
		(0.108)		(0.077)		(0.035)
75+		0.779*		−0.573***		−0.008
		(0.108)		(0.091)		(0.041)
Preferred race category						
White	1.104	1.443	−0.386**	−0.058	0.084	0.127
	(0.424)	(0.467)	(0.183)	(0.227)	(0.078)	(0.127)
Hispanic	0.639	1.863	−0.053	0.607**	0.289**	0.258*
	(0.287)	(0.909)	(0.224)	(0.285)	(0.113)	(0.149)
Black	0.731	1.396	0.128	0.395	−0.149*	0.006
	(0.299)	(0.492)	(0.199)	(0.246)	(0.088)	(0.133)
Asian	1.366	4.161*	−0.568**	−0.076	0.069	−0.160
	(0.709)	(3.071)	(0.249)	(0.361)	(0.108)	(0.196)
Married	0.817	1.055	0.084	0.032	−0.056	−0.026
	(0.123)	(0.107)	(0.070)	(0.065)	(0.043)	(0.031)
Children	0.898**	0.907	−0.030	−0.043	0.009	−0.034
	(0.047)	(0.077)	(0.021)	(0.058)	(0.016)	(0.025)
Education	1.151	1.044	0.199***	−0.093	0.070	0.072**
	(0.171)	(0.101)	(0.063)	(0.066)	(0.043)	(0.031)
Employment status (baseline: Employed)						
Self-employed	2.031***	1.693**	−0.071	−0.286**	−0.133**	−0.118**
	(0.480)	(0.351)	(0.122)	(0.115)	(0.062)	(0.054)
Student	1.475	0.287*	−0.266**	−0.579*	0.059	0.084
	(0.395)	(0.212)	(0.111)	(0.312)	(0.081)	(0.221)
Retired	0.990	0.891	−0.175	0.062	−0.263	0.002
	(1.247)	(0.127)	(0.484)	(0.087)	(0.172)	(0.040)
Out of work	0.914	0.762*	−0.112	−0.211**	−0.013	0.003
	(0.149)	(0.110)	(0.075)	(0.103)	(0.047)	(0.042)
Income level (baseline: < 25 000)						
25 000 $ to 50 000 $	1.410*	1.114	−0.073	−0.029	−0.040	0.064*
	(0.250)	(0.140)	(0.083)	(0.091)	(0.056)	(0.039)
> 50 000 $	2.713***	1.709***	−0.105	−0.021	0.098	0.077*
	(0.580)	(0.255)	(0.092)	(0.093)	(0.060)	(0.047)
Healthcare coverage	0.954	0.904	0.320***	0.372**	0.122*	0.164**
	(0.213)	(0.212)	(0.105)	(0.157)	(0.065)	(0.066)
Subjective health	1.314***	1.660***	−0.029	0.044	−0.026	−0.036***
	(0.088)	(0.082)	(0.029)	(0.032)	(0.018)	(0.013)
Health risks tolerance	0.607***	0.796	0.007	−0.167*	−0.083	−0.127***
	(0.107)	(0.119)	(0.075)	(0.086)	(0.052)	(0.040)
Control for state	Yes	Yes	Yes	Yes	Yes	Yes
N	4 373	7 868	4 373	7 868	4 373	7 868
R^2	0.1308	0.1374	0.082	0.077	0.169	0.141

Note: The significance levels are * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
and standard errors in parenthesis.

Table 2.5: Regressions results for prevention types for women

It is also worth noting that an increase in subjective health is positively correlated with the number of overall preventive activities performed for both men and women above 50 years old.

Model	(16) **OR Behav. < 50 y.o.**	(17) **OR Behav. > 50 y.o.**	(18) **Screen. < 50 y.o.**	(19) **Screen. > 50 y.o.**	(20) **Vacc. < 50 y.o.**	(21) **Vacc. > 50 y.o.**
Interactions						
Behavioral			0.069**	0.067	0.064	0.025
			(0.033)	(0.062)	(0.049)	(0.039)
Screenings	1.422**	1.055			0.230***	0.149***
	(0.250)	(0.131)			(0.038)	(0.034)
Vaccinations	1.387*	1.027	0.122***	0.220***		
	(0.235)	(0.129)	(0.026)	(0.052)		
Control variables						
Caregiver	1.556*	1.151	0.050	0.048	0.060	0.053
	(0.367)	(0.179)	(0.033)	(0.062)	(0.046)	(0.041)
Info. access	1.530**	1.340**	0.042	0.193***	0.006	0.038
	(0.256)	(0.168)	(0.028)	(0.054)	(0.039)	(0.036)
Personal doctor	0.896	1.306	0.311***	0.436***	0.133***	0.191***
	(0.167)	(0.221)	(0.027)	(0.065)	(0.039)	(0.050)
Age (baseline: 18 to 34 y.o. / 50 to 64)						
35 to 49	0.783		0.025		−0.031	
	(0.148)		(0.026)		(0.039)	
65 to 74		1.005		0.132**		0.064
		(0.150)		(0.062)		(0.043)
75+		0.730*		−0.075		−0.010
		(0.126)		(0.075)		(0.053)
Preferred race category						
White	1.199	0.601	−0.161**	−0.024	0.119	0.170
	(0.551)	(0.204)	(0.074)	(0.142)	(0.111)	(0.119)
Hispanic	0.910	0.360**	−0.091	0.113	0.176	0.207
	(0.497)	(0.175)	(0.085)	(0.209)	(0.130)	(0.157)
Black	0.866	0.557	0.049	−0.042	0.003	0.093
	(0.431)	(0.213)	(0.080)	(0.161)	(0.119)	(0.132)
Asian	0.530	1.525	−0.018	−0.426**	−0.182	−0.394**
	(0.297)	(1.037)	(0.102)	(0.177)	(0.154)	(0.186)
Married	0.847	1.057	0.014	0.120**	0.074*	−0.008
	(0.161)	(0.137)	(0.028)	(0.054)	(0.040)	(0.038)
Children	1.038	0.856	−0.012	−0.015	0.003	0.037
	(0.073)	(0.085)	(0.010)	(0.044)	(0.015)	(0.023)
Education	1.925***	2.026***	0.005	−0.027	0.079**	0.097***
	(0.339)	(0.252)	(0.026)	(0.054)	(0.037)	(0.036)
Employment status (baseline: Employed)						
Self−employed	0.810	0.789	−0.028	−0.072	−0.027	−0.052
	(0.188)	(0.153)	(0.038)	(0.071)	(0.046)	(0.051)
Student	2.951***	15.428*	0.137***	−0.374	0.088	−0.418*
	(1.167)	(23.216)	(0.046)	(0.317)	(0.071)	(0.250)
Retired	0.495	0.998	0.069	−0.007	−0.121	0.078*
	(0.409)	(0.173)	(0.166)	(0.066)	(0.244)	(0.047)
Out of work	0.652	0.729	0.243***	0.127	−0.072	−0.009
	(0.185)	(0.155)	(0.046)	(0.097)	(0.071)	(0.066)
Income level (baseline: < 25 000)						
25 000 $ to 50 000 $	1.117	0.908	0.017	−0.069	−0.040	−0.074
	(0.261)	(0.150)	(0.038)	(0.072)	(0.054)	(0.050)
> 50 000 $	2.149***	1.198	0.001	0.031	0.062	−0.041
	(0.574)	(0.224)	(0.036)	(0.078)	(0.056)	(0.054)
Healthcare coverage	0.570**	0.696	0.156***	0.346***	0.027	0.202***
	(0.145)	(0.196)	(0.040)	(0.103)	(0.052)	(0.072)
Subjective health	1.250***	1.461***	−0.014	0.021	0.026	−0.007
	(0.108)	(0.085)	(0.012)	(0.023)	(0.019)	(0.017)
Risk tolerance	0.912	0.779	−0.079***	−0.071	0.042	−0.088**
	(0.180)	(0.122)	(0.030)	(0.069)	(0.041)	(0.045)
Control for state	Yes	Yes	Yes	Yes	Yes	Yes
N	3 719	5 877	3 719	5 877	3 719	5 877
R^2	0.1330	0.1390	0.221	0.097	0.143	0.120

Note: The significance levels are * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
and standard errors in parenthesis.

Table 2.6: Regressions results for prevention types for men

However, when it comes to portfolios of specific preventive behaviors, a decrease in subjective health leads to an increase in the number of vaccinations.

2.3.3 Interaction between preventive activities

For women, health screenings and vaccinations are complementary. A woman of age 50 years or older, who underwent at least one preventive activity in the "vaccination" portfolio during the past 12 months, has a "screenings" portfolio larger, on average, by 0.36 units than a woman who did not, ceteris paribus. Similarly, a woman who is exercising has a larger portfolio of screening activities. This relationship applies the other way round; for example, a woman above 50 years old who underwent a screening is more likely to undergo a vaccination or to exercise. The complementary relationship between health screenings and vaccinations holds for men as well, whereas the complementary relation between exercising and health screenings holds only for men below 50 years old. Exercising and vaccinations, however, present statistically weak results, and no pattern is decipherable.

2.4 Discussions

Our results can be related to previous studies. When it comes to the positive association between being a caregiver and the size of portfolio of preventive activities, our results go along with those of Brown and Brown (2014), who showed that caregiving may yield beneficial health and wellbeing outcomes. One explanation could be that caregiving is associated with more preventive activities. Indeed, caring after dependent individuals seems to raise awareness about potential health problems and the benefit of preventive activities for individuals below 50 years old. Interestingly, this variable stops being relevant for those older than 50. This could occur because individuals of age 50 and above may have already experienced health problems or may have relatives with health problems, hence rendering this feature meaningless. Therefore, raising awareness about health problems among young men tends to increase the number of screenings they perform. Our results also highlight the dominant role of the PD in driving the number of performed preventive activities. These results confirm earlier works on the topic, for instance, those of Qi et al. (2006) showing that in Canada, the presence of a regular medical doctor was associated with increased rates of a specific preventive screening. Additionally to the role of the doctor in the number of preventative activities, can be added the quality of the counseling provided by a medical professional. Indeed, even though they aim for a better health, preventive activities as for instance start exercising, should be done with parsimony. Here lies another role of the doctor or health insurer, in the education of individuals about how these preventative behaviors should be undertaken.

When it comes to sociodemographic drivers, being married increases the portfolio size of preventive activities for men above 50 years old. These results are in line with the observation of Jaffe et al. (2007) and Manzoli et al. (2007), who found that mortality rates were lower for married men. Married women seem to have a positive influence on their spouse in terms of taking care of themselves, and hence, the married men perform more preventive activities. Our findings present a channel through which we observe more longevity for married men, as they perform a

higher number of preventive activities. Health coverage increases the number of cancer screenings and vaccinations, which could be explained by the fact that these preventive activities are medicalized and hence can potentially be reimbursed by insurance. As for the role of subjective health, it seems that younger individuals are less driven by their health when deciding to perform preventive activities. However, subjective health is shown to be negatively associated with the number of vaccinations. This is in accordance with the study by Wu (2003), who showed that respondents with poorer health are more likely to be vaccinated.

Finally, vaccination is shown to be positively associated with screening activities and to a lower extent with exercising. These results confirm that the complementary relationship between preventive activities depends on the nature of the preventive activities considered.

Although we believe that our results provide the right correlations between the variables of interest, one important limitation of our study comes from the cross-sectional nature of our data. Therefore, causation has to be inferred with caution. In addition, our data are based on a survey that contains only self-reported answers, which can entail biases attributed to social desirability and could distort the results (Van de Mortel, 2008; Bauhoff, 2011). Finally, the measurement or nonresponse biases cannot be entirely excluded from any survey ((Schneider et al., 2012).

2.5 Conclusion

Our results offer some valuable insights in terms of prevention-oriented policies. In particular, they highlight the role and quality of health information in driving the overall portfolio of preventive activities. Not only does awareness of health issues play an important role in influencing the number of preventive activities, but, more importantly, the role of health professionals, and in particular the PD, is paramount in that respect. Hence, with the aim of developing preventive activities, PD and other health professionals should communicate further with their patients on the benefits of such behaviors. Furthermore, communication should target single and young individuals on priority, as they are less likely to perform multiple preventive activities than married and older individuals, especially when it comes to screening activities.

Another insight from our results is related to the complementarity between some preventive activities. This complementarity suggests that having performed one specific preventive activity is a cue to action to perform another. Hence, policies promoting vaccinations should also influence the uptake of screenings activities (and vice versa).

Although our results apply to the USA, a comparison between countries is necessary to understand whether our observations are related to a country's healthcare system or deeply rooted in human behavior. In that respect, generalizing our study to Canada, for example, which has a universal single-payer healthcare system very different from the US system but a rather similar culture, would offer a relevant test of our results.

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Chapter 3

How Do Health, Care Services Consumption and Lifestyle Factors Affect the Choice of Health Insurance Plans in Switzerland?

Abstract: In compulsory health insurance in Switzerland, policyholders can choose two main features, the level of deductible and the type of plan. Deductibles can be chosen among six levels which range from CHF 300 and 2 500. While the coverage and benefits are identical, insurers offer several plans where policyholders must first call a medical hotline, consult their family doctor or visit a doctor from a defined network. The main benefit of higher deductibles and insurance plans with limitations is lower premiums. The insureds' decisions to opt for a specific cover depend on observed and unobserved characteristics. The aim of this research is to understand the correlation between insurance plan choices and lifestyle through the state of health and medical care consumption in the setting of Swiss mandatory health insurance. To do so, we account for individual health and medical health care consumption as unobserved variables employing structural equation modeling. Our empirical analysis is based on data from the Swiss Health Survey wherein lifestyle factors like the body mass index, diet, physical activity and commuting mode are available. From the 9 301 recorded observations, we find a positive relationship between having a "healthy" lifestyle, a low consumption of doctors' services and choosing a high deductible as well as an insurance plan with restrictions. Conversely, higher health care services usage triggers the choice of lower deductibles and standard insurance plans.

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3.1 Introduction

Health insurers try to foster healthy lifestyles among their insureds by promoting exercise, supporting fitness center memberships and more recently, the use of wearable connected devices. The data collected from the latter permits insurance companies to track the individual's physical activity, diet or sleep patterns for instance. Subsequently, insureds carrying on a healthy lifestyle benefit from premium discounts or other kinds of monetary rewards. Why health insurers promote a healthy lifestyle is not unfounded. There is a strand of medical literature assessing the effect of the lifestyle on health documenting that a healthier lifestyle leads to a better health relating to lower medical costs (Johansson and Sundquist, 1999; Andersen et al., 2000; Lee and Skerrett, 2001; Joshipura et al., 2001; Penedo and Dahn, 2005; Dauchet et al., 2006; Inyang and Okey-Orji, 2015; Miller et al., 2017). However, the relationship between health and health insurance decisions has been sparsely investigated. While there is a clearly demonstrated link between lifestyle and health in the medical literature, this relation has not been used in actuarial science, leaving the field with little or no evidence of the effect of lifestyle on health insurance decisions.

In our study, using data from the Swiss Health Survey (SHS), we aim to seize the indirect effect of lifestyle – encompassed by the body mass index (BMI), diet, physical activity and commuting mode – on health insurance decisions, i.e., the choice of the plan and the level of deductible. We consider that the decisions are mediated through latent variables linked to health and health care consumption. We set up a structural equation modeling (SEM) framework which allows to capture such indirect effects. We define health as a latent variable embodied by the self-assessed health as well as chronic and limiting in daily activities health conditions. Thereby, the latter offer an objective measure. Further, health directly impacts health care consumption, our second latent variable captured by the number of doctor visits and hospital stays. Additionally, the model is able to account for the bidirectional relationship between health care consumption and the choice of the insurance plan and the deductible level.

The results from our model provide empirical support for the correlation between health insurance choice and lifestyle via health and health care consumption. Using 9 301 observations obtained from the SHS dataset, we control the choice of deductible and insurance plan for socio-economic characteristics (gender, nationality, education, income, number of children in the household, importance of freedom of choice of the specialist doctor, linguistic region and urbanization) and allow for the two endogenous variables to correlate. We show that an increase in age and BMI correlates with a decrease in health, whereas an increase in the number of portions of fruits and vegetables eaten per day, the number of physical activities performed in a week and the usage of a bike to commute correlates with an increase in health. Further results display a negative correlation between health and health care consumption, where the latter variable is positively associated with the choice of a standard, i.e., non-restricting, health insurance plan. Similarly, an increase in health care consumption correlates positively with a low level of deductible. Linking our results, we obtain the indirect effect of lifestyle on insurance

decisions. Thereby, an increase in age and BMI is associated to having a low deductible and opting for a standard insurance plan whereas having a "healthy" lifestyle (good diet and physical activity) correlates with having a high deductible and preferring a more restrictive insurance plan at lower cost.

The remainder of this paper is organized as follows: In Section 2 we briefly review the Swiss health insurance system as well as the literature related to the development of our research hypotheses. In Section 3, we pursue with the set up of the model. Results are displayed along with a discussion in Section 4. Finally, we conclude in Section 5.

3.2 Background Information and Research Hypotheses

3.2.1 Insurance Plans and Deductibles in the Swiss Health System

Before developing our research, we expose some basic features of the Swiss health insurance system that are relevant for the matter of this study. Basic health insurance in Switzerland is mandatory and regulated by Federal law which sets up the reimbursement policies. Beyond the basic plan, individuals can subscribe private complementary health insurance. Regarding the catalog of reimbursements, on the one hand, the basic plan covers basic health risks but does not extend to dental treatments, to alternative medicine techniques, nor to glasses or lenses purchases, exception made for some specific medical conditions. On the other hand, complementary health policies cover the costs that go beyond the basic insurance scheme. In this study, we focus on the decisions in basic health insurance by individuals aged 18 years and older. These individuals face several choices for their insurance plan and deductible level.

Insurance Plans The insurance policies currently offered in Switzerland can be grouped into four families. The first plan is the "standard" plan and it is chosen by most individuals. This policy offers the freedom of choice to visit any doctor or specialist and presents no specific restriction. This plan displays the highest premium. The second most popular plan is the so-called "family doctor" model. Its peculiarity lies in the importance of the general practitioner (GP) that acts as a gatekeeper and centralizes information of the individual. Indeed, holders of this type of policy commit to always consult the same GP in case of any health issues. They have to chose their doctor in advance from a list of recognized GP provided by their health insurer. As a gatekeeper, the GP transfers the patient to a specialist if necessary. This plan typically displays premiums that are 15 to 20% lower than those of standard plans. The third most common plan is known as "CallMed". As its name suggests, this model brings the constraint of calling a medical hotline prior to physically seeking advice from a doctor. Depending on the specific policy rules, there may be an unrestricted choice of the doctor after the phone consultation. Policyholders from this scheme profit from premium reductions of up to 20%. Finally, there is the "HMO" model where the acronym stands for health maintenance organization. Under this model, the

insureds commit to always pass through a doctor affiliated with the selected HMO group for a first consultation. Like in the CallMed model, if necessary, the following consultation may take place outside of the HMO medical team, depending on the health insurer. This last type of plan can come with premiums up to 25% below the standard plan.

Deductible Levels In all insurance plans and on a yearly basis, policyholders chose a deductible. Here, the decision environment is less complex. With amounts regulated by the health insurance law, there exist six levels of deductibles, namely, CHF 300, 500, 1 000, 1 500, 2 000 and 2 500. Once medical costs up to the chosen level are paid out-of-pocket, there only remains a co-payment of 10% up to CHF 700 on the additional costs, whereafter the health insurer entirely reimburses the spendings.

3.2.2 Literature Review and Development of Hypothesis

A recent study conducted by Li et al. (2018) identifies five health risks-reducing lifestyle factors. Among them, three characteristics are of particular interest for our study. Indeed, three lifestyle indicators are found to play a role on mortality. More specifically, life expectancy increases with a BMI ranging between 18.5 and 24.9, 30 minutes or more per day of exercising and a healthy diet. In addition to these measures, we consider in our research another factor: the commuting mode. This variable has been found to be a relevant factor for health conditions in the literature (Oja et al., 1991; Pucher et al., 2010 and Riiser et al., 2018). Since these factors are relatively easily trackable and modifiable, as opposed to, for example, alcohol or tobacco consumption, we use them as determinants for lifestyle.

BMI The effect of BMI on health outcomes has been extensively studied and the results are unambiguous. In reports published as early as 1959, the Society of Actuaries has assessed this link by studying the relationship between mortality rates and weight (Society of Actuaries, 1959; Courtland C. and Edward A., 1979). It was found that as weight increases, so does the mortality rate. Following studies have confirmed and extended on the negative effect of a high BMI on health. Indeed, a higher BMI is associated with a higher risk for coronary heart disease (CHD), cardiovascular disease (CVD) and for congestive health failure (Hubert et al., 1983; Jousilahti et al., 1996). An increase in BMI also increases the vulnerability to endometrial, sigmoidal, colorectal and hormone-related cancer and type II diabetes (non-insuline dependent diabetes mellitus, see Pi-Sunyer, 1991; Le Marchand et al., 1992; World Health Organization, 2000; Stommel and Schoenborn, 2010). Overall, a higher BMI is associated with higher incidence rates of diseases (see also, e.g., Felson et al., 1992; Stommel and Schoenborn, 2010).

Diet The old adage “You are what you eat" has been proven right on multiple stances. Two literature reviews (Block et al., 1992; Steinmetz and Potter, 1996) assess the incidence of fruits

and vegetables intake on several cancers, reporting their protective effect. A healthier diet composed of a greater number of fruits and vegetables decreases the likelihood of cancers like oesophagus, pancreas and breast cancer. Other studies focus on the beneficial impact of an increase of fruits and vegetables consumption on CHD or CVD and report a lowered incidence as well as a declined mortality related to heart deficiencies (Joshipura et al., 2001; Bazzano et al., 2002; Dauchet et al., 2006; Oyebode et al., 2014; Miller et al., 2017).

Physical activity Similarly to the effect of the diet on health, the positive effect of physical activity on health is well established. A literature review conducted by Warburton et al. (2006) assesses 152 studies and highlights that increased levels of physical activity were found to reduce relative risks of death by 20 to 35%, inversely, individuals in the lowest quantiles of physical activity have an increased risk of death from any cause compared to those in the top quantiles. They also account for a reduced incidence of type II diabetes in those individuals who reported weekly physical activity. Other studies also investigated this relationship and back-up Warburton et al. (2006)'s review. Johansson and Sundquist (1999), Lee and Skerrett (2001) and Matthews et al. (2007) associate higher frequency of physical activity to a reduced mortality rate and a better overall health while Gerhardsson et al. (1988), Thune et al. (1997), Thune and Furberg (2001) and Penedo and Dahn (2005) relate a less active lifestyle to increased risks of colon, breast, prostate and colorectal cancers.

Commuting mode The mode of commuting most frequently used to go to work, to school, for groceries shopping or other activities is an integral part of the lifestyle definition. Medical literature especially aimed its attention at walking and cycling as means of transportation. Most papers pool together individuals who walk or cycle to commute and when distinction is made, the results may present slight differences but overall they point out similar effects. For instance, Oja et al. (1991) and Riiser et al. (2018) both find a positive effect of walking or cycling on health measures such as having a high level of good cholesterol (HDL) or a decreased heart rate and systolic tension. The authors also identify an inverse relationship between walking or cycling to work and the risk of having diabetes, results that are equally found by Pucher et al. (2010). Aside from these pooled analyses, the literature review by Oja et al. (1991) focuses on the effect of cycling on health. Of the 16 cycling-specific studies considered therein, all but two show that cycling provides a health benefit and particularly on CVD and CHD risks.

Conjecture 1. An increase in BMI negatively influences health while an increase in fruits and vegetables intake and an increase in physical activity frequency positively relate to health. Walking and cycling for commuting also enhance health.

Health Care Utilization The usage of health care services is most often approximated by the number of doctor visits (GP and specialist), outpatient and inpatient hospitalization or drugs use. In the literature from the medical and economics fields, health care seeking has been

studied under several perspectives, theoretically and empirically (to cite a few Grossman, 1972; Pohlmeier and Ulrich, 1995; Ang, 2010). Many of them address the demand for health care from a socio-economic, including from the insurance point of view. However, health, as a determinant, has seldom been investigated, as the relationship may seem trivial. Fylkesnes (1993) finds that the self-rated health is the most important driver of health care utilization. Another factor which could lead to the increase in health care consumption is the enrollment in health insurance. This incentive effect has been extensively studied and the conclusion is shared among Schmitz (2012) and Prinja et al. (2017)'s literature reviews: insurance take up leads to an increase in health care services utilization. Schmitz (2012) specifies that insurance plans with a deductible lower consumption compared to plans without such a feature. Gardiol et al. (2005) performs this analysis in Switzerland and outlines that 25% of health care expenditures can be attributable to the incentive effect linked to deductibles. Further, alternative plans have been introduced in Switzerland to contain health costs by limiting doctors' visits through the primary usage of telephone hotlines and directing patients to the most efficient doctors' networks. Thus we expect health care utilization to be negatively linked to alternative insurance plans.

Conjecture 2. Health is the most important driver of health care consumption. As health improves, health care consumption declines.

Insurance Demand The empirical literature on health insurance demand is relatively limited. Firstly, health as a component of the decision-making process has been less exploited, probably due to the endogeneity it may present and the difficulty to deal with it. Secondly, papers rather address the demand for complementary (private) health insurance through expected health care expenditures. In our context, we focus on the choices made in a compulsory health insurance environment. Finally, we note that other socio-economic variables have nonetheless been used as drivers of health insurance demand: e.g., gender, age, marital status, country of origin, education, occupation or income (Van de Ven and Van Praag, 1981; Cameron et al., 1988). Among these covariates, it is the effect of income that has been the most extensively estimated (see Schneider, 2004, for a literature review). It is needless to emphasize on the lack of empirical evidence linking health and health insurance demand, let alone the effect of lifestyle. Our research aims at providing an instance of the relationship between lifestyle and health insurance demand via the health and health care consumption channels.

Conjecture 3. The effect of socio-economic covariates, namely, gender, education and income on decisions for the insurance plan and the deductible is significant.

Linking the arguments on health, health care utilization and insurance demand, we further propose the following conjecture:

Conjecture 4. The effect of health through health care consumption is believed to be significant on the health insurance decisions. Higher health care usage is associated with a low deductible and a standard insurance plan.

3.3 Model Framework and Available Data

3.3.1 Structural Equation Model

To study the above questions and conjectures, the choice of SEM is guided by the several advantages that this technique presents. Health is a difficult concept to quantify and is oftentimes estimated by its outcomes, namely chronic disease occurrence or mortality rates. This method, however, does not provide a complete nor a sufficient picture of the individual's state of physical and mental well-being. In view of these elements, in our SEM model, we let health be a latent variable, influenced by the lifestyle. Doing so, we avoid by the same occasion any reporting bias and measurement errors of health-related variables (on which Crossley and Kennedy (2002) shed light). Indeed, some authors use the self-assessed health of the individual as a proxy for the unobserved health, especially in the labour market field (Haan and Myck, 2009; Strully, 2009; Böckerman and Ilmakunnas, 2009, for a few examples). The issue in this procedure lies in the unobserved characteristics such as risk aversion which may, for instance, affect both the own health perception and health insurance demand. Solely relying on the self-reported health as the face value of health is also prone to severe measurement biases highlighted in the literature (mostly attributed to social desirability, discussed in Huang et al., 1998 and Van de Mortel, 2008). In a SEM setting, on the contrary, health can be captured by several more objective measures called manifest variables and by this mean minimize the bias. The same rationale applies to the latent variable of health care seeking. Like health, the unobservable variable of the demand of health care services is a difficult notion to grasp by a single variable or even a set (as for instance in Bourne et al., 2009) and may be subject to omitted variables bias. Again, SEM is well-suited for using several variables at once to define the concept.

Additionally from dealing with the above issues, SEM can indicate simultaneous direct relationships called paths. These paths can be specified as well between exogenous as between endogenous variables, thus allowing for a more thorough and exhaustive analysis. Because of this convenient ability of the model to assess the simultaneous relationship between multiple unobserved variables and observed outcomes, SEM frameworks have been widely used in sociology- and psychology-related literature (Sobel, 1987; Cuttance and Ecob, 2009; MacCallum and Austin, 2000; Martens, 2005). Moreover, we note that usual econometric methodologies like fixed effects regressions cannot be applied in our context due to the cross-sectional nature of data from surveys. In a SEM, the estimation of the parameters comes from a maximization of likelihood between the actual covariance matrices of the relationships between variables and the estimated covariance matrices of the model (for more information see Bollen, 1989).

Our research aims to assess the relationship between lifestyle and health insurance decisions. Figure 7.1 gives a graphical representation of the model that we employ. We measure lifestyle from four behaviors, namely BMI (BMI), diet (DIT), sport (SPT) and commuting modes (CMW, CMB, CMP, CMV), while we control for age (AGE). In our model, however, lifestyle is not assumed to have a direct effect on insurance decisions (insurance plan PLN and deductible

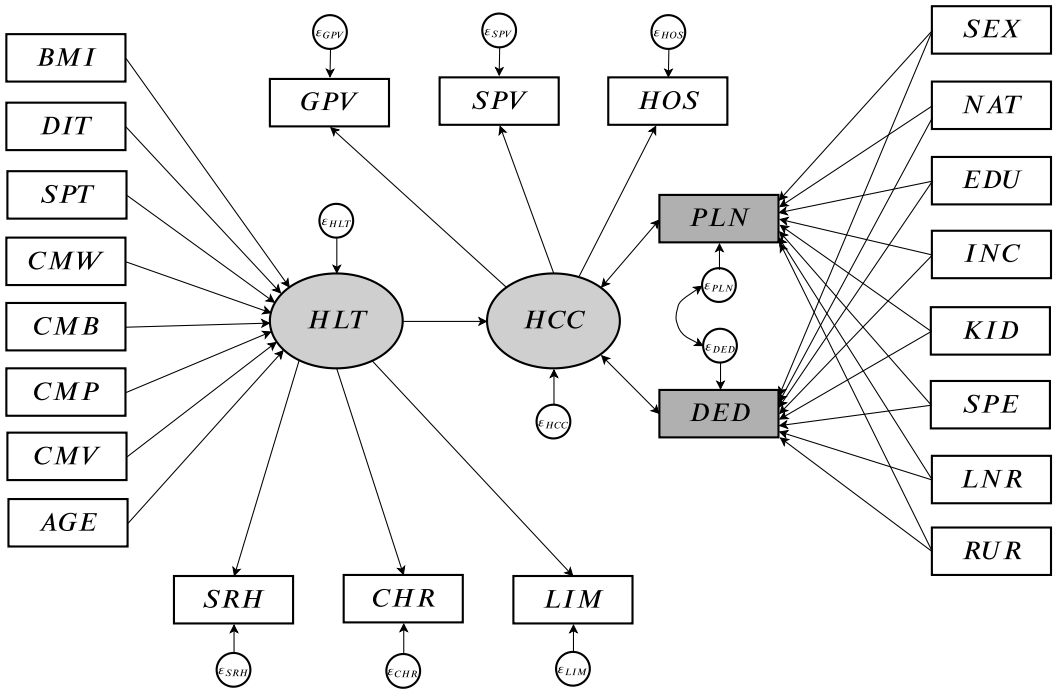

Figure 3.1: Illustration of the path diagram of the structural equation model.

DED) but rather an indirect one mediated via health (HLT) and health care consumption (HCC). Health is hypothesized to play a role on health care usage, which in turn is conjectured to drive health insurance decisions, thus creating a bridge with the lifestyle. Finally, the health insurance choice is controlled for by socio-demographic characteristics (gender SEX, nationality NAT, education EDU and income INC levels, number of children in the household KID, freedom of choice for specialist doctors SPE, language region LNR and urbanicity RUR). Further, health is measured using information on self-reported health SRH, chronic health conditions CHR and limiting health conditions LIM, while health care consumtion is evalauted from GP visits (GPV), specialist and gynaecologist visits (SPV) and hospital stays (HOS). In Table 3.1 we summarize and describe the variables that we use.

Measurement of Health To run the analysis, we design our model with health (HLT) as a latent variable. This latent variable is measured by three observed variables: the self-rated health (SRH), having or having had a chronic health condition lasting at least six months (CHR) and having limiting health conditions in daily activities during the past six months (LIM). These three indicators are assumed to perfectly correlate with the unobserved health variable. We consider the following set of equations:

$$\begin{aligned} SRH_i &= \kappa_{SRH} HLT_i + \varepsilon_{SRH,i} \\ CHR_i &= \kappa_{CHR} HLT_i + \varepsilon_{CHR,i} \\ LIM_i &= \kappa_{LIM} HLT_i + \varepsilon_{LIM,i} \end{aligned} \tag{3.1}$$

Variables	Type	Description	Values
AGE	Exogenous	Age	integer (19+)
BMI	Exogenous	BMI according to WHO scale	categories: 0 – 18.4, 18.5 – 24.9, 25 – 29.9, 30+
DIT	Exogenous	Diet, portions of fruits and vegetables consumed on average per day	categories: 0 – 2, 3 – 4, 5+
SPT	Exogenous	Sport sessions with perspiration, per week	categories: 0, 1 – 2, 3+
CMW	Exogenous	Commuting mode – walking	no, yes
CMB	Exogenous	Commuting mode – biking	no, yes
CMP	Exogenous	Commuting mode – public transportation	no, yes
CMV	Exogenous	Commuting mode – motorized vehicle	no, yes
HLT	Latent	Health	–
SRH	Manifest	Self-reported health, (Likert scale)	0 (very bad), 0.25 (bad), 0.5 (average), 0.75 (good), 1 (very good)
CHR	Manifest	Chronic health conditions lasting at least 6 months	no, yes
LIM	Manifest	Limiting health conditions in everyday activities	no, yes
HCC	Latent	Health care consumption	–
GPV	Manifest	Number of general practitioner and family doctor visits in the past 12 months	integer
SPV	Manifest	Specialist and gynaecologist visits in the past 12 months	integer
HOS	Manifest	Any hospital stays of at least one night	no, yes
SEX	Exogenous	Gender	male, female
NAT	Exogenous	Nationality	Swiss, other
EDU	Exogenous	Level of education	primary, secondary (professional and general), tertiary (professional and general)
INC	Exogenous	Level of income in CHF	categories: 0 – 3 000, 3 001 – 4 500, 4 501 – 6 000, 6 001+
KID	Exogenous	Number of children in household < 18 y.o.	categories: 0, 1, 2, 3, 4+
SPE	Exogenous	Freedom of choice of specialist important	no, yes
LNR	Exogenous	Language region	German, French, Italian
RUR	Exogenous	Rural region	no, yes
PLN	Endogenous	Insurance plan	standard, other (HMO, family doctor, telmed, other)
DED	Endogenous	Deductible in CHF	high (2 500), low (300)

Table 3.1: Description of the variables used in the model.

In the system of Equations (3.1), κ_{SRH}, κ_{CHR} and κ_{LIM} are the loading factors. The $\varepsilon_{.,i}$ are the error terms for the individual i linked to each of the indicator variables. For our modeling, we assume the error terms to be uncorrelated with each other and with the latent variable HLT as well as having an expectation value of zero.

Regression Model for Health The following Equation (3.2) describes the regression of health on the lifestyle variables including a control for age as depicted in the left-hand part of the graph in Figure 7.1.

$$\begin{aligned} HLT_i = \beta_0 + \beta_{AGE} AGE_i + \beta_{BMI} BMI_i + \beta_{DIT} DIT_i + \beta_{SPT} SPT_i + \beta_{CMW} CMW_i \\ + \beta_{CMB} CMB_i + \beta_{CMP} CMP_i + \beta_{CMV} CMV_i + \varepsilon_{HLT,i} \end{aligned} \tag{3.2}$$

The respective β_0 and $\beta_.$ coefficients correspond to the baseline respectively the regression coefficients linked to the variables. The error term $\varepsilon_{HLT,i}$ is assumed to have a zero expected value and to be uncorrelated with the error terms in the other submodels.

Measurement of Health Care Consumption Our second latent variable is the individual's inherent health care consumption (HCC). Three variables are used to approximate this

behavior: the number of GP or family doctor visits (GPV), the number of specialists visits (SPV) and whether the respondent had an inpatient hospitalization (HOS). All three variables are accounted for during the past 12 months and are assumed to perfectly correlate with our unobserved health variable.

$$\begin{aligned} GPV_i &= \lambda_{GPV} HCC_i + \varepsilon_{GPV,i}, \\ SPV_i &= \lambda_{SPV} HCC_i + \varepsilon_{SPV,i}, \\ HOS_i &= \lambda_{HOS} HCC_i + \varepsilon_{HOS,i} \end{aligned} \tag{3.3}$$

In the system of Equations (3.3), λ_{GPV}, λ_{SPV} and λ_{HOS} are the loading factors. The $\varepsilon_{.,i}$ denote the error terms for the individual i in each indicator variable. The errors are assumed to be uncorrelated with each other and with the latent variable HCC. Errors are supposed to have an expected value of zero.

Regression Model for Health Care Consumption The following Equation (3.4) is the regression of health care consumption on health (HLT) and the insurance characteristics (plan PLN and deductible DED):

$$HCC_i = \delta_0 + \delta_{HLT} HLT_i + \delta_{PLN} PLN_i + \delta_{DED} DED_i + \varepsilon_{HCC,i} \tag{3.4}$$

The respective δ_0 and $\delta_.$ coefficients correspond to the baseline respectively the variables' regression coefficients. The error term $\varepsilon_{HCC,i}$ is assumed to have a zero expected value and to be uncorrelated with other error terms.

Regression Models for Health Insurance Decisions The two following regressions express the choice of the insurance plan (PLN) and deductible level (DED) according to health care consumption and socio-demographic characteristics. The variable PLN takes the value of 1 if the respondent chooses an alternative plan (HMO, family doctor, telmed, other) and 0 for the standard plan. Concerning the deductible levels DED, if the individual has opted for a yearly deductible of CHF 300, the variable takes the value of 0. The value is 1 if the chosen deductible is CHF 2 500. Here we build a simple model by selecting only the two extreme values because we consider that they unveil a clear choice towards the highest versus the lowest coverage. We will disregard all individuals with other choices. The resulting respective probit models (choices 0 and 1) are modeled through latent variables. Indeed, for our SEM we suppose there exist auxiliary random variables PLN^* and DED^* such that:

$$\begin{aligned} PLN_i^* = \gamma_0^{PLN} &+ \gamma_{HCC}^{PLN} \cdot HCC_i + \gamma_{SEX}^{PLN} \cdot SEX_i + \gamma_{NAT}^{PLN} \cdot NAT_i + \gamma_{EDU}^{PLN} \cdot EDU_i + \gamma_{INC}^{PLN} \cdot INC_i \\ &+ \gamma_{KID}^{PLN} \cdot KID_i + \gamma_{SPE}^{PLN} \cdot SPE_i + \gamma_{LNR}^{PLN} \cdot LNR_i + \gamma_{RUR}^{PLN} \cdot RUR_i + \varepsilon_{PLN,i} \end{aligned} \tag{3.5}$$

and

$$DED_i^* = \gamma_0^{DED} + \gamma_{HCC}^{DED} \cdot HCC_i + \gamma_{SEX}^{DED} \cdot SEX_i + \gamma_{NAT}^{DED} \cdot NAT_i + \gamma_{EDU}^{DED} \cdot EDU_i + \gamma_{INC}^{DED} \cdot INC_i + \gamma_{KID}^{DED} \cdot KID_i + \gamma_{SPE}^{DED} \cdot SPE_i + \gamma_{LNR}^{DED} \cdot LNR_i + \gamma_{RUR}^{DED} \cdot RUR_i + \varepsilon_{DED,i} \tag{3.6}$$

for which we have PLN and DED variables acting as indicators:

$$PLN_i = \begin{cases} 1 & \text{if } PLN_i^* > 0 \\ 0 & \text{otherwise} \end{cases} \tag{3.7}$$

and

$$DED_i = \begin{cases} 1 & \text{if } DED_i^* > 0 \\ 0 & \text{otherwise} \end{cases} \tag{3.8}$$

The values γ_0^{PLN} and $\gamma_\cdot^{PLN}$ respectively γ_0^{DED} and $\gamma_\cdot^{DED}$ follow the standard notations for regression coefficients. Further, the error terms $\varepsilon_{PLN,i}$ and $\varepsilon_{DED,i}$ are assumed to come from a standard normal distribution and are allowed to correlate with each other.

3.3.2 Swiss Health Survey Data

We base our study on data obtained from the Swiss Health Survey, a cross-sectional nation-wide survey (Swiss Federal Statistical Office, 2019; Swiss Federal Statistical Office, 2018).[1] The survey is carried out by the Swiss Federal Statistical Office on behalf of the Federal Council every five years since 1992. In the following, we use the wave of 2017 which is the sixth and most recent one. The survey responses are firstly collected via computer-assisted telephone interviews and followed up by an additional written questionnaire available in the three official Swiss languages (German, French and Italian). The included population is aged 15 years or over and lives in Switzerland in a private household. The total sample of 2017 includes 22 134 telephone interviews and 18 832 subsequently completed and returned questionnaires. The information collected concerns the state of health of each individual (e.g., physical and mental well-being, health conditions, health limitations), the use of health care (e.g., doctor consultations, hospitalization, use of drugs), the health insurance status (e.g., insurance plan, deductible, purchase of complementary insurance), behaviors susceptible to have an influence on health (e.g., alcohol intake, drug consumption) and socio-demographic characteristics (e.g., employment status, income, nationality).

To conduct our empirical analysis, we extract a sample of "complete" answers comprising 9 301 observations. The completeness of an observation is defined by the absence of not available (NA) entries. We can consider that the NAs are distributed randomly across the original data since our extracted sample is not markedly different from the original one. Regrading the lifestyle indicators, our final sample has a slightly higher median age, i.e. 52 versus 49 years. As long as it concerns the BMI, the diet (number of portions of fruits and vegetables eaten per day) or

[1] See `www.bfs.admin.ch/bfs/fr/home/statistiques/sante/enquetes/sgb.html`.

the frequency of physical activity[2] and commuting, the average values and shares are very close. Regarding the other exogenous variables, the original sample displays the same level of self-rated health (good), and a smaller percentage has limiting in daily activities health conditions which is most probably due to a lower proportion of individuals aged over 50 years ; our final sample contains a higher number of individuals with chronic health conditions. Overall, we consider that our extracted sample does not present any selection bias thanks to the sampling performed beforehand by the Swiss Federal Statistical Office and the relatively large sample size when compare to other surveys (where the number of observations is often considerably smaller).

3.3.3 Descriptive Statistics

Exogenous Characteristics Affecting Health In Table 3.2, we present some descriptive statistics based on our data along the variables appearing in our hypotheses. The lifestyle is conjectured to have an effect on health, which is defined in our model by the self-rated health (SRH), the past or ongoing existence of a chronic disease lasting for six months or more (CHR) and a health condition coming with a limitation in daily activities (LIM). Subsequently, through health, they impact health care consumption, gauged in our model by the number of GP visits (GPV), the number of specialists visits (SPV, gynaecologists excluded, to avoid pregnancy-related bias) and the individual's hospital stays of one night or over (HOS). The first column in Table 3.2 counts the number of observations N per category in each variable while the second represents the corresponding share from the whole sample of 9 301 observations (total N). The other six columns display the mean for each manifest variable. Over the total sample (cf. last row of the table), the mean self-rated health is at 0.81, that is, a good health on average, 35% of the sample's population reported chronic and 21% limiting in daily activities health conditions. Alongside, the average number of GP visits is 2.27 and the number of visits to specialists is 1.99. Finally, 18% of the sampled individuals have stayed in a hospital for more than one night during the 12 months preceding the survey.

Concerning the lifestyle variables, when grouping individuals by BMI categories, we decipher the pattern that is documented in the literature, i.e., respondents with a BMI comprised between 18.5 and 24.9 declare the highest self-rated health (0.84) and the lowest propensity of having a chronic or a limiting health condition (0.31 and 0.18). Additionally, as the BMI increases, the SRH decreases (from 0.84 to 0.72 for the category with highest BMI) and the proportion of individuals having chronic or limiting health conditions increases (moving from 0.31 and 0.18 to 0.50 and 0.30 for CHR respectively LIM in the group with highest BMI), thus matching observations from the literature (cf. Section 6.2). An increase in BMI is also positively associated with health care services utilization. According to our descriptive statistics, the effect of the diet on the health and health care usage proxies is mitigated. Two associations can be made: an increase of the number of fruits and vegetables eaten on average per day comes with an increase in self-rated health (0.80 to 0.83) but also with an increase of visits to specialists (1.33 to 1.66).

[2]Note that we have excluded individuals not being able to walk at least 200m by themselves.

	N	(%)	SRH	CHR	LIM	GPV	SPV	HOS
BMI								
0 – 18.4	260	(2.8)	0.82	0.35	0.20	2.10	1.72	0.12
18.5 – 24.9	5 075	(54.6)	0.84	0.31	0.18	1.99	1.37	0.10
25.0 – 29.9	2 973	(32.0)	0.79	0.37	0.22	2.36	1.42	0.12
30.0+	993	(10.7)	0.72	0.50	0.30	3.42	1.76	0.17
Diet								
0 – 2 portions per day	4 309	(46.3)	0.80	0.35	0.21	2.33	1.30	0.12
3 – 4 portions per day	3 043	(32.7)	0.82	0.35	0.20	2.15	1.49	0.11
5+ portions per day	1 949	(21.0)	0.83	0.35	0.21	2.30	1.66	0.11
Sport								
No activity	2 947	(31.7)	0.74	0.42	0.26	2.91	1.72	0.14
1 – 2 times per week	3 641	(39.1)	0.84	0.33	0.18	1.92	1.24	0.10
3+ times per week	2 713	(29.2)	0.85	0.30	0.18	2.02	1.39	0.11
Commuting – walking								
No	4 732	(50.9)	0.81	0.34	0.20	2.28	1.46	0.11
Yes	4 569	(49.1)	0.81	0.36	0.21	2.25	1.42	0.11
Commuting – biking								
No	6 892	(74.1)	0.80	0.36	0.21	2.42	1.48	0.12
Yes	2 409	(25.9)	0.85	0.33	0.19	1.82	1.32	0.09
Commuting – public transport								
No	6 000	(64.5)	0.81	0.34	0.20	2.30	1.38	0.12
Yes	3 301	(35.5)	0.81	0.36	0.22	2.21	1.54	0.11
Commuting – motorized vehicle								
No	3 092	(33.2)	0.81	0.35	0.21	2.23	1.50	0.11
Yes	6 209	(66.8)	0.81	0.35	0.21	2.28	1.41	0.11
Age								
19 – 26	568	(6.1)	0.87	0.21	0.14	1.95	1.20	0.08
25 – 40	2 117	(22.8)	0.87	0.23	0.13	1.80	1.38	0.11
41 – 50	1 732	(18.6)	0.83	0.29	0.17	1.86	1.15	0.09
51 – 60	1 840	(19.8)	0.79	0.38	0.21	2.28	1.71	0.10
61 – 70	1 552	(16.7)	0.77	0.46	0.26	2.58	1.55	0.13
71 – 80	1 173	(12.6)	0.75	0.48	0.31	3.06	1.61	0.17
81+	319	(3.4)	0.72	0.45	0.36	3.55	1.06	0.15
Total	9 301	(100.0)	0.81	0.35	0.21	2.27	1.99	0.18

Table 3.2: Descriptive statistics of the exogenous characteristics affecting health.

Further analysis, including the study of significance, will be performed in our SEM. When it comes to physical activity, however, the relationship seems indisputable. As the frequency of sports activities increases, the data present a clear increase in the self-rated health variable (0.74 to 0.85), coupled with a decrease in the occurrence of health conditions (0.42 to 0.30 for CHR and 0.26 to 0.18 for LIM). This beneficial association continues on health care seeking through all indicators where we observe declining consumption. Concerning the effect on the commuting mode, we observe that it largely depends on the type. Biking as a mean of transportation exhibits the most notable link to our indicators: individuals who bike report a higher self-rated health (0.85 against 0.80), a lower in-group propensity to have a chronic or limiting health condition (0.33 versus 0.36 for CHR and 0.19 versus 0.21 for LIM). By the same token, the

number of GP visits drops from 2.42 to 1.82 on average, the number of visits to specialists from 1.48 to 1.32 and the inpatient stays go down by 3 percentage points. Finally, age displays the expected effect, that is, as age increases, the self-rated health decreases and the propensity in each category of having a chronic or a limiting health condition increases, along with the frequency of all medical visits. Finally, to supplement our descriptive statistics, we document in Table 3.3 the correlation coefficients between our proxy variables as well as their standard deviations.

	SRH	CHR	LIM	GPV	SPV	HOS
SRH	1.00	−0.58	−0.50	−0.53	−0.46	−0.31
CHR	−0.58	1.00	0.49	0.35	0.27	0.14
LIM	−0.50	0.49	1.00	0.27	0.18	0.15
GPV	−0.53	0.35	0.27	1.00	0.51	0.39
SPV	−0.46	0.27	0.18	0.51	1.00	0.33
HOS	−0.31	0.14	0.15	0.39	0.33	1.00
Std. dev.	0.19	0.48	0.40	3.85	3.86	0.32

Table 3.3: Correlation coefficients and standard deviation of the indicator variables.

Exogenous Characteristics Affecting Health Insurance Decisions In the following Table 3.4, we provide an overview of the distribution of the observations along the second set of exogenous variables, i.e. the socio-demographic characteristics, linked to insurance decision. We provide the shares of individuals along the insurance plan and deductible choices. Additionally to the control variables, we present the distribution along health and health care utilization indicator variables.

Firstly, when comparing the statistics of health insurance decisions based on socio-demographic variables, we observe several trends. Between both genders, we note one important difference with women being more likely to chose a lower deductible when compared to men (65.9% of the women, 52.2% of the men). Regarding the nationality, Swiss nationals tend to opt more often for an alternative plan whereas non-Swiss individuals rather go for the standard one. Education, income and the number of children in the household seem to demonstrate differences. As the level of education, income or the number of children increases, the majority switches from the low to the high level of deductible. Moreover, increasing education levels come along with a favor for alternative insurance plans. Along the two other variables, the majority already favors alternative plans with a slight increase in the share as income and number of children get higher. Finally, the last markedly different result with respect to the socio-demographic variables is the specificity of German-speaking respondents regarding the choice of the insurance plan: most individuals from the German-speaking language area tend towards alternative models which is not the case in the French and Italian-speaking regions.

Secondly, when focusing on health-related variables, we observe that higher levels of self-rated health go along with individuals that have chosen the high level deductible as well as an al-

			Insurance plan		Deductible	
	N	(%)	Std. (%)	Oth. (%)	Low (%)	High (%)
Gender						
Male	4 343	(46.7)	43.9	56.1	52.2	47.8
Female	4 958	(53.3)	43.1	56.9	65.9	34.1
Nationality (baseline: Swiss)						
Swiss	7 633	(82.1)	40.7	59.3	60.3	39.7
Other	1 668	(17.9)	55.8	44.2	55.6	44.4
Education						
Primary	1 152	(12.4)	55.2	44.8	83.4	16.6
Secondary – professional	3 384	(36.4)	44.6	55.4	68.0	32.0
Secondary – general	1 213	(13.0)	43.9	56.1	57.0	43.0
Tertiary – professional	1 280	(13.8)	33.8	66.2	50.9	49.1
Tertiary – general	2 261	(24.3)	40.6	59.4	40.7	59.3
Income						
0 – 3 000	3 502	(37.7)	45.8	54.2	70.1	29.9
3 001 – 4 500	1 949	(21.0)	45.9	54.1	64.5	35.5
4 501 – 6 000	1 738	(18.7)	39.8	60.2	54.0	46.0
6 001+	2 112	(22.7)	40.2	59.8	41.7	58.3
Children in household						
0	6 720	(72.3)	45.6	54.4	65.9	34.1
1	354	(3.8)	42.1	57.9	56.8	43.2
2	774	(8.3)	42.4	57.6	45.1	54.9
3	220	(2.4)	43.6	56.4	47.3	52.7
4+	1 233	(13.3)	32.5	67.5	36.4	63.6
Freedom of choice of specialist important						
No	2 436	(26.2)	33.9	66.1	52.4	47.6
Yes	6 865	(73.8)	46.8	53.2	62.0	38.0
Language region						
German	6 273	(67.4)	39.0	61.0	60.1	39.9
French	2 295	(24.7)	52.6	47.4	58.8	41.2
Italian	733	(7.9)	53.1	46.9	56.3	43.7
Rural region						
No	6 412	(68.9)	44.6	55.4	59.5	40.5
Yes	2 889	(31.1)	40.9	59.1	59.4	40.6
Self-rated health						
Very bad	32	(0.3)	46.9	53.1	87.5	12.5
Bad	212	(2.3)	57.5	42.5	93.4	6.6
Average	1 020	(11.0)	51.9	48.1	90.3	9.7
Good	4 218	(45.3)	43.2	56.8	66.6	33.4
Very good	3 819	(41.1)	40.6	59.4	41.2	58.8
Chronic health conditions						
No	6 062	(65.2)	43.3	56.7	49.7	50.3
Yes	3 239	(34.8)	43.7	56.3	77.8	22.2
Limiting health conditions						
No	7 385	(79.4)	43.2	56.8	54.5	45.5
Yes	1 916	(20.6)	44.5	55.5	78.5	21.5
Visits to general practitioner						
0	2 623	(28.2)	43.0	57.0	36.6	63.4
1	2 459	(26.4)	41.7	58.3	54.0	46.0
2 – 3	2 503	(26.9)	43.9	56.1	71.5	28.5
4+	1 716	(18.4)	45.9	54.1	84.8	15.2
Visits to specialist						
0	5 111	(55.0)	42.7	57.3	50.0	50.0
1	1 977	(21.3)	42.1	57.9	64.9	35.1
2 – 3	1 265	(13.6)	44.6	55.4	74.6	25.4
4+	948	(10.2)	48.6	51.4	78.7	21.3
Hospital inpatient stay						
No	8 243	(88.6)	43.3	56.7	57.3	42.7
Yes	1 058	(11.4)	44.3	55.7	76.5	23.5
Total	9 301	(100.0)	59.5	40.5	43.4	56.6

Table 3.4: Descriptive statistics of the exogenous characteristics affecting insurance decisions.

ternative insurance plan. This observation is not at odds with economic logic as an individual with a lower self-rated health may expect to have higher yearly expenses and hence would prefer to pick a model with a higher coverage. The same observation can be drawn for individuals disclosing chronic or other limiting health conditions. The distribution of individuals who do not report having or having had any chronic health conditions is fairly even among both models (43.3% standard) and deductible levels (49.7% low). For individuals with a limiting health condition, the figures are still very similar. When focusing on people reporting any chronic or limiting health conditions, the shares regarding the model choices remain in fact relatively stable but present a strong increase in the share opting for the low deductible, i.e., 77.8% for CHR and 78.5% for LIM.

Finally, concerning our manifest variables accounting for health care consumption, the observations meet economic intuition. Regarding the models, the relationship is constant, as the number of visits, disregarding the type of doctor, increases, health care consumption does too. Respondents typically favor an alternative insurance plan. Strong differences appear with regard to the deductible. As an example, individuals not reporting any visits to GP are 36.6% in the low deductible category; this percentage rises to 84.4% for those reporting four visits or more during the past 12 months. The same pattern can be observed throughout all the three variables.

3.4 Model Results and Discussion

In this section, we document the SEM results for our health measurement for the model defined through Equation (3.1), followed by the regression model for health, i.e., the coefficients of the lifestyle effects on health (see Equation 3.2), the health care consumption measurement as modeled through Equation (3.3) succeeded by the health care consumption regression (Equation 3.4). Finally, we present the results for the regression models on health insurance demand for both insurance plan (Equation 3.5) and deductible (Equation 3.6).

We estimate the SEM using diagonally weighted least squares, which best fits binary observed variables as it does not make any distributional assumptions nor considers continuity contrary to the maximum likelihood method (for more information see Muthén, 1984 or Li, 2016). To run our empirical analysis, we make use of the *lavaan* package in R (Rosseel, 2012). Before presenting the model results and coefficients, we lay out the goodness-of-fit measures. The measures and indicators calculated for the overall model are the following. We obtain a Comparative Fit Index (CFI) of 0.959 and a Tucker-Lewis Index (TLI) of 0.995 for the incremental fit measures and a Root Mean Square Error of the Approximation (RMSEA) of 0.028 and a Standardized Root Mean Square Residual (SRMR) of 0.043 for the absolute fit indices. According to Hooper et al. (2008)'s cut-off values our model presents a good fit and an RMSEA lower than 0.03, as in our case, is indicative of an excellent fit. In the following paragraphs and the Tables 3.5 to 3.9, we display our results.

Measurement of Health Our first results are on the establishment of the health latent variable. We set the loading factor κ_{SRH} to one as it sets the scale of the HLT variable. The model results in Table 3.5 lay out that, expectedly, as individuals report chronic or limiting health conditions, their health significantly decreases. Indeed both variables CHR and LIM are highly significant at the 0.001 p-level and the related κ coefficients are negative.

	Health measurement	
	κ	Sig.
$SRH_i \sim \kappa_{SRH} HLT_i$	1.000	
$CHR_i \sim \kappa_{CHR} HLT_i$	−1.760	***
$LIM_i \sim \kappa_{LIM} HLT_i$	−1.047	***

Note: . $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3.5: Results for the measurement of health (Equation 3.1).

Regression Model for Health In Table 3.6 we report the coefficients stemming from the regression Equation (3.2), i.e., the results for the effect of lifestyle-defining behavior on the latent health variables. The first variable of interest is the BMI and the displayed results are in line with the existing literature. The baseline category is a BMI ranging from 18.5 and 24.9 and shows no statistical difference with the lower category of BMI. However, when moving to higher categories, the obtained regression coefficients suggest that the negative effect on health becomes more salient: the value of coefficient is multiplied by a factor of three between the third and last group, both coefficients being highly significant at the 0.001 level. Regarding the diet variable which is characterized by the number of fruits and vegetables eaten on average per day, there is no strong effect in our sample. The only change in health may occur from an increase from 0 – 2 portions per day to 3 – 4 resulting in an increase with a 0.1 significance level. This result is somehow expected from our descriptive statistics where no striking differences between the several categories have been observed. Sport activities when compared to the baseline of no activity are significantly linked to better health. When comparing individuals performing 1 – 2 sessions or 3+ sessions per week with the baseline, we observe very similar coefficient values. That is, an increase in the number of sessions enhances health rather similarly between both categories with a coefficient of 0.053 (1 – 2 sessions) respectively 0.057 (3+ sessions). We note that our findings concerning diet and sport are found to follow the same pattern as in Blanchard et al. (2004). Indeed, they found that among cancer survivors, individuals following the five fruits and vegetables per day recommendation did not witness an increase in their health-related quality of life contrary to individuals who performed physical activities. If we classify the commuting modes according to their impact on health, biking would be the most interesting way of transportation in this regard and walking would come second. The stronger effect of biking rather than walking has also been documented by Matthews et al. (2007). Using a motorized vehicle is still linked to higher health but with a lower significance (p-value of 0.1), using public transport is linked to lower health (significance level 0.1). Finally, with increasing age, individuals relate to lower health levels. Overall, having a BMI lower than 25, eating 3 to 4

	Health	
	β	Sig.
BMI category (baseline: 18.5 – 24.9)		
0 – 18.4	−0.016	
25.0 – 29.9	−0.032	***
30.0+	−0.090	***
Diet (baseline: 0 – 2 portions per day)		
3 – 4 portions per day	0.007	.
5+ portions per day	0.002	
Sport (baseline: No activity)		
1 – 2 times per week	0.053	***
3+ times per week	0.057	***
Commuting mode – walking (baseline: No)		
Yes	0.010	*
Commuting mode – biking (baseline: No)		
Yes	0.016	***
Commuting mode – public transport (baseline: No)		
Yes	−0.008	.
Commuting mode – motorized vehicle (baseline: No)		
Yes	0.008	.
Age (baseline: 25 – 40)		
19 – 24	−0.001	
41 – 50	−0.029	***
51 – 60	−0.061	***
61 – 70	−0.080	***
71 – 80	−0.103	***
81+	−0.107	***

Note: . $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3.6: Results for the regression model for health (Equation 3.2).

portions of fruits and vegetables per day on average, exercising with perspiration at least once per week and biking or walking as a way to commute represents a lifestyle relating to better health. In the opposite, having a high BMI, a greens-deprived diet as well as a sedentary lifestyle links to lower health levels. These results support and specify our first conjecture.

Measurement of Health Care Consumption Moving to the second latent variable construction defined in Equation (3.3), we set the loading factor λ_{GPV} to one defining the scale of the health care consumption variable HCC. From the results in Table 3.7 one can observe a positive relationship between the number of visits to specialist doctors or inpatient stays and health care consumption (both with p-level 0.001).

Regression Model for Health Care Consumption In Table 3.8, we display the results of the variables conjectured to affect health care consumption. Undoubtedly, health has the strongest impact on health care consumption. Indeed the health variable is highly significant

	Health care consumption measurement	
	λ	Sig.
$GPV_i \sim \lambda_{GPV} HCC_i$	1.000	
$SPV_i \sim \lambda_{SPV} HCC_i$	0.828	***
$HOS_i \sim \lambda_{HOS} HCC_i$	0.042	***

Note: . $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3.7: Results for the measurement of health care consumption (Equation 3.3).

at the 0.001 p-value level and shows a negative sign, i.e., better health comes with lower care consumption. This confirms the second conjecture. Further, we find that the type of plan as well as the level of deductible play a role in the amount of health care services used. These results are to be compared with the actuarial literature (to cite a few: Cameron et al., 1988; Gardiol et al., 2005; Schmitz, 2012 or Prinja et al., 2017). Our results suggest that an alternative insurance plan and a high level of deductible are related to higher health care consumption. These results are counterintuitive since higher deductibles and alternative insurance plans are thought to diminish care service utilization. Indeed, care must be taken when concluding with our findings since significance levels for both variables are much less convincing then the one for the health indicator. The results also contradict our findings from the "reverse" regression models in Equations (3.5) and (3.6) where we consider health care consumption as a predictor for insurance plan and deductible decisions (see below). Further, a step for explaining the relationship of the deductible with consumption might be that individuals who already experience expenses reaching the deductible of CHF 2 500 may want "to make the most out of it" and use more services that they have been postponing beforehand due to their high level of deductible. Thus, people who chose a level of CHF 300 may have less incentives to "overuse" health care services as they have a lower contract level that is fairly easily attained within a year. At this stage, we remain with the one conclusion that health status is probably the single primary driver for health care consumption.

	Health care consumption	
	δ	Sig.
Health		
	−14.109	***
Insurance plan (baseline: Standard)		
Other	0.096	.
Deductible (baseline: Low)		
High	0.284	*

Note: . $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3.8: Results for the regression model for health care consumption (Equation 3.4).

Regression Models for Health Insurance Decisions Finally, we now turn to the probit regression models defined in Equations (3.5) and (3.6) linking the previously discussed variables

and results to health insurance decisions. The results are presented in Table 3.9. We consider two insurance decisions. The first column of the table reports the coefficients of the model related to the decision of choosing an alternative or "other" insurance plan (versus the baseline of the standard plan). The second part of the table relates to choosing the high deductible (versus the baseline of the low deductible). The first and foremost result concerns health care consumption. For both the alternative insurance plan and the high level of deductible choices, HCC displays a negative sign with statistical significance above 0.001. This means that higher care utilization goes along with the choice of the standard insurance plan and the low deductible. This confirms our fourth conjecture. It is noteworthy that both coefficients are statistically very strong (as it is for example the case of health on health care consumption in Table 3.8). Assembling the results from the entire model, we can put forward the following reasoning: when we define a healthy lifestyle as having a low BMI, a diet of 3+ portions of fruits and vegetables per day, practicing sports or commuting by bike or walking, such lifestyle enhances health; higher levels of health are associated with lower health care consumption which in turn correlates with the choice of an alternative insurance model and a high deductible.

This observation can provide an empirical application to several theoretical concepts. The foundational paper of Ehrlich and Becker, 1972 investigates the interaction between market insurance, self-insurance and self-protection. The authors argue that self-protection and market-insurance can be complementary, unless when the price of market insurance (here, the premium) is independent of the expenditure on self-protection (here, the healthy lifestyle). In our case, it is the latter that takes place. Indeed, as highlighted earlier, in the creation of a contract for mandatory health insurance in Switzerland, no other information than age and zip code is taken into account. Hence, the price of the premium is independent of the level of health and lifestyle (i.e. self-protection). As per the above-mentioned theoretical research, a healthy lifestyle should hence be negatively correlated with the choice of an insurance. If we pose the choice of insurance in our framework as being the selection of the lowest deductible combined with the standard health insurance plan, then the theory holds in our empirical analysis. Indeed, via a decreased healthcare consumption, self-protection (defined as a healthy lifestyle) leads to the choice of a higher level of deductible as well as an alternative plan (defined as a lower level of insurance). Such a behaviour can also be associated to two other concepts in insurance theory: moral-hazard and adverse-selection (Arrow, 1963). The former is defined as a change in behaviour following the adoption of insurance that may lead to an increased probability of the adverse event to happen. Translated to our case, this would mean to stop exercising or eating healthy because of the existence of health insurance in case of a health issue. The latter is defined in a context where the health insurer does not have perfect information on the insured. In our framework, this is indeed the case, as the health insurer does not have any knowledge about the state of health of the insured. This asymmetry of information gives rise to the selection of the highest level of insurance by the population that is the most risky (Pauly, 1978). The regression results of our survey concur with the theory. We find that as health care consumption increases, so does the likelihood to choose the lowest level of deductible and the standard insurance plan, i.e. a higher level of coverage.

	"Other" insurance plan		"High" deductible	
	γ	Sig.	γ	Sig.
Health care consumption				
	−0.030	***	−0.308	***
Gender (baseline: Male)				
Female	0.059	.	−0.405	***
Nationality (baseline: Swiss)				
Other	−0.362	***	−0.060	
Education (baseline: Primary)				
Secondary – professional	0.198	***	0.462	***
Secondary – general	0.105	*	0.271	***
Tertiary – professional	0.314	***	0.486	***
Tertiary – general	0.191	***	0.627	***
Income (baseline: 0 − 3 000)				
3 001 – 4 500	0.003		−0.001	
4 501 – 6 000	0.064		0.052	
6 001+	−0.004		0.229	***
Children in household (baseline: 0)				
1	0.067		-0.108	
2	0.058		0.021	
3	−0.005		0.039	
4+	0.201	***	0.115	*
Freedom of choice of specialist important (baseline: No)				
Yes	−0.317	***	−0.268	***
Language region (baseline: German)				
French	−0.284	***	0.064	.
Italian	−0.235	***	0.258	***
Rural region (baseline: No)				
Yes	0.059	.	0.099	**

Note: . $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3.9: Results for regression models for health insurance demand (Equations 3.5 and 3.6).

Regarding the further control variables, we find several significant relationships that support conjecture three. For example, we observe that women rather tend to prefer a low level of deductible when compared to men. Another notable difference lies in the choice of the insurance plan regarding the nationality: non-Swiss individuals rather select a standard insurance plan while Swiss individuals, who might be more knowledgeable about the system and have a family doctor, rather go for other plans (p-value 0.001). Next, an increase in the level of education correlates with the choice of an alternative insurance plan and a higher level of deductible. This might correlate with better system understanding or potentially an interaction with better health. Similarly, individuals from very high income classes rather select a higher deductible. This somewhat unexpected observation about wealthier families opting for the higher level of deductible may be explained by two factors. Firstly, in Switzerland health insurance subsidies are commonplace and they may incentivize the uptake of a lower deductible. The second element could be the diminishing level of risk-aversion with wealth. As highlighted by, e.g., Schnei-

der (2004), less wealthy households may be more risk-averse than wealthier ones as unexpected medical expenses could push them into financial distress. Concerning the number of children in the household, only the last category is markedly different with larger households going for the less expensive alternative plan and the high deductible. Further, we find that respondents for whom the freedom of choice for the specialist doctor is important prefer the standard insurance plan and a low level of deductible. This is intuitive. Finally, our geographical control variables highlight the cultural differences between German-speaking respondents and French or Italian-speaking ones as the latter are associated with the choice of a standard plan and a high deductible (as seen already from the descriptive statistics). Regarding rural regions, individuals are more prone to choose an alternative insurance plan coupled with a high deductible.

3.5 Concluding Remarks

Using data from the Swiss Health Survey, we successfully establish the relationship between lifestyle-defining behavior and decisions in a compulsory health insurance environment. Employing a structural equation model with health and health care consumption characterized by latent variables, we make proof for the following conjectures. Firstly, we empirically demonstrate that an increase in BMI is negatively correlated with health whereas an increase in fruits and vegetables intake, as well as an increase in the number of sport sessions with perspiration are linked to better health. Additionally, we find that biking and walking for commuting are also related to better health. On a second instance, our results indicate health as being the most significant driver of health care consumption. In a third step, we confirm that socio-economic as well as geographic covariates play a role in health insurance decisions. Finally, we are able to document the positive relationship between the choice of an alternative health insurance plan coupled with a high deductible in the case where health care consumption is lower. Bridging the different findings, we understand that health-enhancing behavior correlates with a decreased health care services consumption, the choice of an alternative health insurance plan and a high level of deductible.

Our research binds medical and actuarial aspects to provide a better understanding of health insurance. Most of the results are intuitive, but have not been researched so far for significance in a regression framework. Our results, although, are very specific to the Swiss health insurance scheme and conclusions have to be drawn carefully. For further comprehension of the decision-process, it may be interesting to perform analyses under other insurance environments as well as make use of panel data, where available, for the implementation of other econometric techniques.

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Chapter 4

Challenges and Solutions for Integrating and Financing Personalized Medicine in Healthcare Systems: A Systematic Literature Review

Abstract: The scope and ambitions of biomedical institutions worldwide currently working toward the integration of personalized medicine (PM) require recognizing the potential profound impact on regulatory standards and on the economic functioning and financing of healthcare. Against this background, researchers and policymakers must manage the arising challenges for the healthcare systems. In this paper we study the literature related to the consequences of PM on health insurance and care systems. Using the PRISMA research protocol, we search the existing body of literature and analyze publications dealing with insurance (419 papers) in the field of PM. After a detailed reading of the 52 studies included in our analysis, we synthesize challenges in three fields that must be addressed to avoid hindering the implantation of PM. The key issues that we highlight concern (1) a lack of clear and consistent data on the economic relevance of PM, (2) a value-oriented and cost-efficient definition of reimbursement thresholds, (3) the implementation of PM in the prevailing healthcare system. In the meantime, we provide several solutions to these concerns; we present (a) risk-sharing contracts that can deal with the emerging coverage challenges, (b) criteria that could constitute future reimbursement thresholds and (c) examples of successful implementations of PM into healthcare systems. Our findings are relevant for policymakers and health insurance companies for redefining the guidelines for the healthcare schemes of the future.

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CDx	Companion diagnostics
CED	Contract with evidence development
HTA	Health technology assessment
MCDA	Multiple criteria decision analysis
MEA	Managed entry agreement
NGS	Next generation sequencing
NHS	National Health Service
NICE	National Institute for Health and Care Excellence
PAS	Patient access scheme
PGx	Pharmacogenomics / Pharmacogenetics
PM	Personalized medicine
PRISMA	Preferred reporting items for systematic reviews and meta-analysis
PVA	Price-volume agreement
QALY	Quality-adjusted life year
RSA	Risk-sharing agreement
WTP	Willingness-to-pay

List of acronyms.

4.1 Introduction

Personalized, stratified, precision or genomic medicine bear the same logic: a particular problem requires a tailored solution, i.e. a specific genetic mutation leading to a health condition should be treated with a specific drug. The often costly trial-to-error paradigm leading to adverse drug responses (Spear et al., 2001, Sultana et al., 2013) is being slowly replaced by a data-based optimization of resources that we refer to with personalized medicine (PM)[1]. In the prevailing procedures, the time, health and energy wasted as well by doctors as by patients in an iterative search of the best drug response translates into expenses paid by the sponsors, i.e. insurers, governments or private payers. Fast forward twenty years, with PM, before a patient starts his/her course of treatment, we determine which drug will lead to the best outcome and minimize the risks of adverse events. Doctors have access to the necessary medical data of the patient on the spot with the implementation of electronic health records (Henry et al., 2016). Individuals have the possibility of having their DNA sequenced to draw a risk profile for the most common afflictions as well as personal at-risk conditions (Hammond, 2020). Finally, combining all the flows of health-related data (such as information collected from wearable devices) with gene mutations, research hubs gain a more precise and accurate knowledge, which is clinically applied. Going back to the present, we already have the technology for a fast, cheap and accurate DNA sequencing. For instance, next generation sequencing technology (NGS) has replaced the Sanger method, resulting in the cost of a whole genome sequencing drastically decreased with a cutback in prices by two hundred times in only ten years, decreasing from roughly USD 200 000 in 2009 to less than USD 1 000 in May 2020 (National Human Genome Research Institute, 2020). Smart wearable devices are continuously collecting data (Dunn et al., 2018) laying the ground for a common database that will consolidate genetic, metabolic and lifestyle data. Now, for clinical integration of PM to become reality, the most important hurdle is not of scientific nature but rather economic and behavioral or systemic.

Payers, i.e., governments, insurers and patients, are key to completely unlock PM's systematic use in the healthcare system. Financial cover for personalized drugs and genetic sequencing is, nonetheless, yet unestablished with the institutional payers that are in the scope of our study. Such payers are typically the government when regarding health insurance in terms of social insurance or the private insurers when looking at private health insurance coverage. Today, most often we lack commonly accepted figures on clinical utility and cost-efficiency of PM. This renders insurers rather skeptical (Cohen et al., 2013, Trosman et al., 2015, Messner et al., 2016) and keeping policymakers from listing such drugs and treatments in the catalog of what social security and social health insurance cover. Additionally, as we are still in the infancy of PM, payers must invest in the short term but the benefits are to be reaped in the long run. This is especially critical in (private) insurance contracts where patients can switch their insurance provider and thus deter companies to consider longer terms. To counter the paucity of cost-efficiency evidence, "first-mover" payers are needed to cover the treatments and to generate

[1] A full list of the acronyms is available in the Appendix.

enough data. Thereby, governments and pharmaceutical companies may play an important role since private insurers tend to selectively only cover proven drugs. Indeed, one key challenge is to provide a mean to generate data and knowledge while limiting costs.

In this systematic literature review, we analyze the different challenges for integrating PM into healthcare systems from the payers' perspective. The viewpoint and the obstacles that payers stumble upon when it comes to financing PM have seldom been investigated. This paper fills this gap and gathers the extant body of knowledge. After a presentation of the methodology used for selecting articles in Section 4.2, the remainder of this paper logically follows the challenges faced by the payers when assessing PM. In Section 4.3, we document the economic relevance of PM with an emphasis on the lack of evidence and the potential remedies to the issue. In Section 4.4, we expose the governance challenges that impede PM coverage with a selection of possible solutions to tackle them. Finally, in Section 4.5, we develop on what characteristics slow down the integration of PM into the healthcare system and how to overcome them. We conclude the paper with a discussion in Section 4.6. In the Appendix we provide a comprehensive synopsis of the reviewed papers.

4.2 Methodology

4.2.1 Review Strategy

To conduct our literature review, we use the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol (Moher et al., 2015). To build the initial catalog of publications for review, we search the Web of Science Core Collection database.[2] The extraction of bibliography entries is performed on the 28th October 2019. Thereby, we have included all available literature (published from 1900 onward) in all languages.

Our systematic review consists of the five steps outlined in Figure 4.1. The original corpus of publications is extracted from Web of Science considering all documents referring to personalized health or healthcare, respectively to precision, individualized, personalized, stratified or genetic medicine. Further, we require the results to contain a link to health insurance, payers or reimbursements.[3] To be exhaustive, we include the various spellings of PM as well as words affiliated to the same concept of medicine (Pokorska-Bocci et al., 2014). In this first step we identify 419 records for further screening.

[2]The Web of Science Core Collection is a curated bibliographic database containing peer-reviewed scholarly journals, books and conference proceedings published worldwide in the sciences, social sciences, and arts & humanities disciplines. It is available at `http://isiknowledge.com/wos`.

[3]The full query used is as follows: `(ALL = ‘‘personalized health OR ALL= ‘‘personalized health OR ALL= ‘‘personalized healthcare OR ALL= ‘‘personalised healthcare OR ALL= ‘‘personalized health care OR ALL= ‘‘personalised health care OR ALL= ‘‘precision medicine OR ALL= ‘‘individualized medicine OR ALL= ‘‘individualised medicine OR ALL= ‘‘personalized medicine OR ALL= ‘‘personalised medicine OR ALL= ‘‘stratified medicine OR ALL= ‘‘genetic medicine OR ALL= ‘‘genomic medicine) AND (ALL = ‘‘health insur* OR ALL= ‘‘payer* OR ALL =‘‘reimbursement)`.

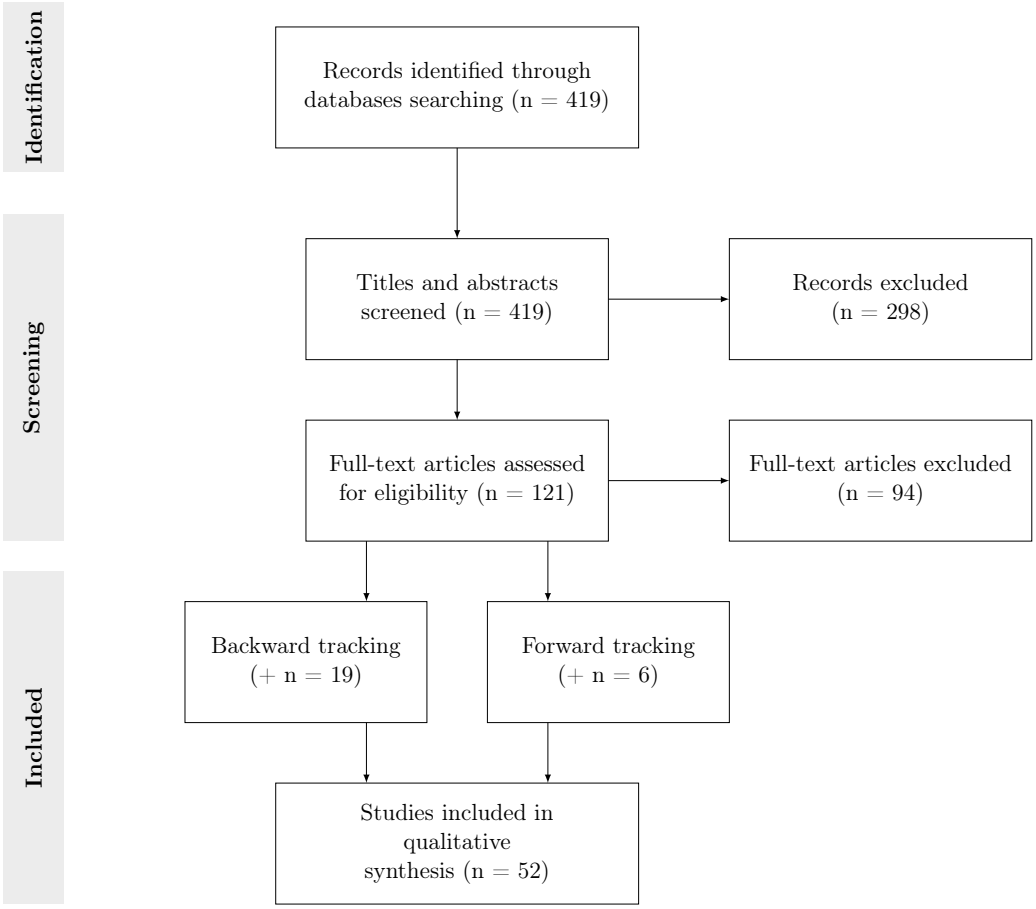

Figure 4.1: PRISMA review protocol based on Moher et al. (2015).

In the second and third steps of the protocol, we manually scan the titles and abstracts. In the selection process, we retain literature relevant to one of our themes of interest, i.e., the payment for PM, the existence of reimbursement strategies, and the implementation of PM into the current health insurance paradigm. We exclude 298 records that are not in the scope of our review. The assessment of the eligibility of the full text of the remaining 121 publications yields 94 exclusions. Subsequently, the fourth and fifth steps consist of backward and forward tracking. In backward tracking, we browse the bibliography of the 27 retained publications to select citations that are beyond the selection criteria of our first step but relevant for the review. Regarding forward tracking, we investigate Google Scholar relevant publications that cite one of the retained articles from the third step. In the Appendix we summarize the reviewed papers along their focus, the methodology used, and the key contents with the main provided results.

Throughout the scanning of the literature, we outline three major topics. All relevant literature is falling into at least one of the following subjects:

1. **Economic Relevance of PM.** Insurers as rational economic agents need proof of the cost-effectiveness of PM technologies before granting coverage. We include all literature that provides evidence, economic indicators related to PM, and tools and methods to foster the building of evidence. This includes but is not restricted to the two major approaches, i.e.,

contracts between manufacturers and payers to generate the evidence and standardization of data provision by assessment bodies.

2. **Governance Challenges.** In this stream we include literature that tackles the heterogeneity for inter- and intra-countries PM coverage. This includes, for example, papers that highlight the emerging discrepancies from the existence of a myriad of contracts, the standardization of reimbursement thresholds, and the need for enhanced communication between stakeholders.

3. **Healthcare System Implementation.** Here, we are interested in all actionable ideas to overcome the hurdles linked to, e.g., technology and pricing, that impede a successful implementation in current healthcare systems. Insights to overcome these obstacles include for example risk-sharing or evidence development contracts between manufacturers and payers.

The first author handled the selection and scoping of the papers. The second author conducted the proof-reading to validate the collection. In case of disagreement, both authors discussed and reached a consensus. Additionally, both authors carried out a synopsis of the reviewed papers by extracting for each paper the region under study, the methodology used, the key contents and main results as well as the main topics the paper addresses.

4.2.2 Synopsis of the Results

Throughout the review that we present in detail in the following sections, we observe several recurring issues that the institutional payers face when dealing with PM. These challenges cover three dimensions – economic relevance (see Section 4.3), governance (Section 4.4) and implementation in the healthcare system (Section 4.5). Put briefly, the available evidence of economic efficiency is thin, of heterogeneous quality and assessed using too many different *ad hoc* metrics. This hurdle impedes or delays coverage and patient access to PM. To overcome this, potential solutions include manufacturer-payer partnerships and public subsidies to generate evidence, coupled with the establishment of universal health technology assessment (HTA) methodologies, the harmonization of guidelines and the economic requirements to address data quality. The second obstacle is the observed heterogeneity in coverage for PM technologies on various levels, internationally, as well as at the countries' scale. This can be attributed to multiple factors, among them a lack of standardization as highlighted above, the existence of a myriad of payer-manufacturer contracts and the in place national healthcare scheme. Possible manners to unify coverage are the centralization of HTA to exclude discrepancies, clearer communication among stakeholders and the sharing of information beyond country borders. Finally, an assessment of the characteristics of PM highlights the underlying difficulties that payers encounter. Among them, we find that gene-based tests and diagnostics are deemed as experimental or investigational and without a clear actionable outcome. High costs also often characterize PM technologies along with a difficulty to predict future expenses. To tackle this final issue, diverse

approaches are possible. While few authors emphasize on the necessity to move to value-based pricing and coverage, others present numerous means to alleviate the financial burden of PM (e.g., multiyear contracts, health currency and government interventions). Authors also expose rather successful examples of PM inclusion in the healthcare system with payer-manufacturer partnerships such as price-volume agreements, usage caps or pay-for-performance contracts.

4.3 Economic Relevance: Lack of Evidence and Efficiency Metrics

4.3.1 Description of the Challenges

PM is an emerging field and as of today, we do not have enough hindsight about its economic relevance. The insufficient amount of documentation regarding real-world data, i.e. the cost-effectiveness of a personalized drug or treatment after its implementation into clinical practice, is highlighted in the literature. For instance, Terkola et al. (2017) conduct a literature review to identify studies that confront randomized controlled trial results (performed before the introduction of the drug) with later-obtained data from clinical practice: they find such studies nonexistent. A large number of papers they reviewed either emphasize this issue or ask the reader to bear it in mind. Among the 26 papers mentioning economic relevance, more than 60% bring up the lack of studies assessing the applicability of PM. While some articles simply mention the issue (Degtiar, 2017; Amendola et al., 2019), others blame the paucity of evidence as being one of the hurdles the field must overcome to enable an optimal coverage (Deverka et al., 2007; Sullivan et al., 2011; Faulkner et al., 2012; Fugel et al., 2012; Hresko and Haga, 2012; Cohen et al., 2013; Terkola et al., 2017). Without clear documentation on the cost-effectiveness of PM, payers do not have any incentive to reimburse it as it is not proven to make sense economically. Alongside this uncertainty, payers admit being skeptical regarding the clinical usefulness of PM drugs and technologies. In the paper by Graf et al. (2013), 50% of the assessed private payers report the need of evidence for clinical utility. On this topic, we observe a particular focus on pharmacogenomic/pharmacogenetic tests (PGx) and companion diagnostics (CDx). These tests link the individual's genetic variations to drug responses to provide the optimal drug and determine the appropriate dosage. The same ascertainment is made by Deverka (2009) in an overview of evidence for PGx. The drug management following the CDx, i.e. the effective use of the right drug at the right dosage to maximize efficacy, is questioned. Several other authors account for this issue, among them Deverka et al. (2007), Meckley and Neumann (2010), Sullivan et al. (2011), Hresko and Haga (2012), Faulkner et al. (2012), Cohen et al. (2013), Merlin et al. (2013), Towse and Garrison (2013), Cohen and Felix (2014), Terkola et al. (2017), Phillips et al. (2017) and Lu et al. (2018b). The unclear outcome of PGx, CDx testing or more broadly PM, holds payers back from covering such procedures. There remains a high level of uncertainty about the compliance of the patient or health practitioner to the results of the CDx or PGx tests and to a more efficient drug use.

Regarding current available evidence, it is rather scare, heterogeneous in terms of quality and used metrics, and payers consider it as insufficient to offer coverage. There is no universal evidentiary standard and authors navigate through cost-utility and cost-effectiveness analysis with various outputs like, for example, cost per quality-adjusted life years (QALY), cost per life years gained or incremental cost-effectiveness ratio (Simeonidis et al., 2019). HTA is a process designed to appraise the value of a drug or technology by asserting its cost-effectiveness, safety, clinical utility, and, when considered, social aspects. The outcome of the evaluation serves decision-makers regarding coverage and reimbursement. So far, despite the efforts of several HTA agencies such as the National Institute for Health and Care Excellence (NICE) in the United Kingdom, the Haute Authorité de Santé (HAS) in France or the Institute for Quality and Economic Efficiency in Healthcare (IQWiG) in Germany, no standard framework has been adopted. In a systematic review of pharmacogenetic and genomic screening programs, Vegter et al. (2008) underline the absence of standardization in HTA among the reviewed studies. The Lancet Oncology Commission comes to the same conclusion regarding cost-effectiveness analysis of PGx and adds that this lack of harmonization hinders reimbursement (Sullivan et al., 2011). In the following years, authors point out the lack of a clear evidentiary framework in PM. According to Hall and McCabe (2013), "the standards for establishing evidence on effectiveness and cost-effectiveness of personalized medicine technologies are considerably less well-defined than those for conventional health technologies". In their literature review, Knowles et al. (2017) report that 16% of the assessed papers are discussing "conflicting and unclear evidentiary standards in regulations". The same observation is made by Miller et al. (2011), Faulkner et al. (2012), Fugel et al. (2012), Messner et al. (2016), Knowles et al. (2017) and Simeonidis et al. (2019). When there is no governmental institution for the HTA, each payer has its cost-effectiveness and clinical utility standards and without a clear framework for assessing PM, the field presents heterogeneous evidence. Finally, Meckley and Neumann (2010) conclude their case study on six paired genetic tests and treatments by understanding that "more generous reimbursement of PM technology likely awaits more high-quality evidence", thereby summarizing both obstacles, the quantity of cost-efficiency data and its quality.

4.3.2 Discussion of Potential Solutions

We group possible ways to deal with the aforementioned issues in two approaches: top-down and bottom-up. The top-down approach consists of establishing standards for the HTA at a national or international level. The bottom-up approach resides in the creation of data through contracts between payers and manufacturers. Each approach tackles the issue differently. On the one hand, by standardizing the HTA, manufacturers will present harmonized evidence, which is of equal, deemed sufficient, quality to be assessed and the product to access the market. Subsequently, the payers will have access to these data and be able to make a well-informed decision. On the other hand, if the partnership alternative is favored, the data generated via these contracts will correspond exactly to the needs of the payer to assess the cost-efficiency or value of a particular drug or technology.

From the reviewed papers, Miller et al. (2011), Garfield (2011), Payne and Annemans (2013), Vozikis et al. (2016), Lu et al. (2018a), Lu et al. (2018b) and Simeonidis et al. (2019) agree on the standardization of HTA to be a valid solution. Be it on an international level (Terkola et al., 2017), European level for European Union countries (Garfield, 2011) or at a national level. They assert that the benefit of standardization would lie in a harmonized and clear regulation of economic requirements for the HTA agencies to follow, thus facilitating the assessment process. Knowles et al. (2017) take a step further and recommend an alignment between regulators and payers on data specification. Both measures, the standardization of economic requirements and the alignment between stakeholders will homogenize the requirements and the assessment process to develop a common evidence base. The United Kingdom is a good example of HTA process standardization where NICE is responsible for assessing both efficacy and efficiency of a treatment, to subsequently give recommendations for its administration by the National Health Service (NHS). NICE's cost-effectiveness threshold ranges from £20 000 to £30 000 per QALY (McCabe et al., 2008). Only if a drug is below the threshold, it is recommended for the provision by the NHS. In a comparative assessment of European reimbursement systems conducted on behalf of the Personalized Medicine Coalition, Garfield (2011) grades ten countries' market access for PM technologies. Among the evaluated European countries, the United Kingdom received the best score in two criteria, the HTA process for diagnostics and the HTA process for companion products, confirming the straightforward nature of the appraisal process. Finally, Miller et al. (2011) qualify the United Kingdom's practices as "perhaps the best developed technology evaluation and medico-economic assessment system". The United Kingdom, thus, illustrates a successful standardization of the HTA process.

Regarding the bottom-up approach, there are several manners to constitute quality real-world data that are already in place for similar issues touching any drug. Thomas et al. (2010) suggest that reimbursement systems should foster evidence development. The first method is to find coverage with evidence development (CED) agreements. CEDs are contracts between a payer and a manufacturer, where the former commits to provide its members temporary coverage for an "investigational" or "experimental" drug or technology. In return, the latter must enroll these members in a payer-approved clinical program destined to generate enough evidence for the payer to make an informed decision about the continuation of the coverage (Garrison et al., 2013; Akhmetov and Bubnov, 2017; Lu et al., 2018b). The use of CEDs permits the generation of real-world data that are then used to compute the final cost-effectiveness estimate. This type of contract is in use for "regular" drugs in several countries like Sweden or the Netherlands where, according to Ferrario and Kanavos (2015), there were 29 and 52 CEDs, respectively, in 2015. The Netherlands has been a recurring example of public-private partnerships between payers and manufacturers (Garrison et al., 2013; Ferrario and Kanavos, 2015; Faulkner et al., 2016; Akhmetov and Bubnov, 2017). In both the Netherlands and Sweden, however, these contracts are not used at first instance, they are introduced after a drug's inconclusive results of efficacy or high price. In other countries, these agreements are also expanding. In a survey conducted by Cohen and Felix (2014) among Medicare payers, 9 out of 11 responded that they would adopt CED contracts to build improved evidence for CDx. However, even though authors are enthusiastic

about the issues this form of partnership addresses (Sullivan et al., 2011; Chalkidou and Rawlins, 2011; Hresko and Haga, 2012), they must be used with caution as CEDs do have several drawbacks. First, it is unclear who should bear the financial burden of demonstrating the clinical utility. Lu et al. (2018b) state that the costs would remain with the manufacturer. However, according to Lu et al. (2015) for instance, the Australian government has funded evidence generation in the past, and manufacturers did not share the costs. Subsequently, as reported by Garrison et al. (2013), in the United States, drugs on CED contracts between Medicare and manufacturers have not been de-listed even after being proved to offer only little advantage with the potential cost of increased risk of mortality. Boon et al. (2015) make a similar observation in The Netherlands. In a subsample of 46 orphan drugs, none of them have been de-listed even if showing little evidence of cost-effectiveness. Besides the fact that the delay for evidence building (four years in The Netherlands for instance) is considered as rather short, pressure from the public and ethics makes the de-listing on the sole cost-effectiveness criteria difficult. Finally, Garrison et al. (2013) point out the importance of a well-defined contract between the two parties as both may engage in suboptimal behavior. The conditions regarding the outcomes must be specified, such as the price discount, if the drug does not meet the target or in case of delay of data delivery.

Another manner to promote data collection is to resort to public financing. Several authors emphasize on the role of the government in the provision of healthcare (Vozikis et al., 2016) and hence its participation in evidence generation. Deverka (2009) and Towse and Garrison (2013) suggest the participation of the State by subsidies or public investments while Simeonidis et al. (2019) propose that "State-owned research institutions and universities" work along the private sector.

Finally, a third solution arises through data sharing. Lu et al. (2018b) propose a collaborative model, which collects and shares all existing health data. Thereby, they envision to use existing data from electronic health records and merge them with clinical outcomes from genetic interventions and insurance claims to obtain a comprehensive flow of information. The idea is to get large national databases containing genotype-phenotype-linked information. Such database would enable the combination of genetic data through test results and further costs from the usage of these tests through insurance claims.

Despite the relative novelty of the field, some solutions to current issues are present. The quality of the evidence of the cost-effectiveness of PM can be tackled by harmonization of HTA processes at an international scale, whereas specific coverage agreements can promote further evidence generation.

4.4 Governance: Heterogeneity in Coverage

4.4.1 Description of the Challenges

PM being in its infancy, policymakers and insurers only slowly adapt their coverage guidelines. A few papers review the patient reimbursement systems and coverage for PM technologies of European countries. When comparing reimbursement strategies, Garfield (2011) notes that each country has a specific HTA and reimbursement process. Because of these disparities, Miller et al. (2011) describe the European HTA system as decentralized, hence less effective, and qualify the market penetration of PM as "minimal". In subsequent studies, Fugel et al. (2012) and Payne and Annemans (2013) still observe substantial differences in coverage among European countries and others in the world (Degtiar, 2017).

On closer inspection, this heterogeneity is present in countries sharing some common characteristics. For example, Italy and Germany have been mentioned to have discrepancies in reimbursement and coverage strategies because of their decentralized healthcare systems. Garfield (2011) presents the example of these specific countries where there is a significant difference among regions in terms of coverage for PM. The author further exposes that in Europe, reimbursement and HTA schemes can be made either nationally or regionally whereas regulatory decisions are made at the largest level, centrally or nationally. This creates delays and eventually inconsistencies in the coverage and reimbursement within a country. At a finer granularity, this observation is shared for the United States as well by Deverka (2009), Hresko and Haga (2012) and Lu et al. (2018a). The case of the United States is slightly different because besides the diversity along the states there is another level of decision-making. Indeed, each payer has its own guidelines and evaluation of PM – which translates into coverage disparities among public and private stakeholders.

The discrepancies in coverage can be attributed to the heterogeneous regulation. To decide whether to cover a PM drug or technology, social insurance needs besides sufficient evidence, to refer to established guidelines. Trosman et al. (2010) in their article understand that the variation in coverage among payers depends on the type of evidence used and the perception of this evidence. Based on findings from Schwarzer et al. (2015) and Simeonidis et al. (2019), there is no PM-specific willingess-to-pay (WTP) threshold, i.e. the highest price at which payers are willing to reimburse a medicine or test. Without such benchmark, each drug is assessed separately and by different criteria by each HTA institution.

On the country level, another source for disparities in the coverage is that assessment processes are not standardized. Fugel et al. (2012) add for the case of diagnostics that "there is no clear and consistent process for value assessment" in Western Europe and in the United States when compared to what is already in place in the United Kingdom with NICE. Following the results of a policy Delphi panel, Messner et al. (2016) report that among 19 overall challenges for the clinical adoption of NGS, the foremost issue is that "different payers have different

evidentiary standards for assessing clinical utility, leading to inconsistent policies on coverage and reimbursement for NGS-based testing".

Another reason explaining the existence of such disparities is the myriad of risk-sharing agreements (RSA, also called managed entry agreements, MEA, or patient access schemes, PAS). Briefly put, RSAs are contracts between a manufacturer and a payer designed to ease the integration of a specific drug or technology in clinical practice. The sharing of the risk lies in the payment amount, which is made dependent either on the clinical outcome, e.g., increase in QALYs and reduction of side-effects, or the economic outcome linked to the cost-effectiveness of the technology. This outcome, which triggers and defines the price of the treatment, is agreed upon before signing the contract. This arrangement mitigates the risk taken by the payer on financing a treatment, which has not strictly proven effective yet (Antonanzas et al., 2019). Further, according to Antonanzas et al. (2019), another way of splitting risk is for the payer to co-finance additional evidence generation in exchange of patient treatment access to meet the requirements for cost-efficiency proof. These contracts can be diverse: some are conditional reimbursements such as CEDs seen previously, others are price-volume agreements. Different countries have different priorities, e.g., the generation of evidence or accessibility of a drug, resulting in tailored agreements designed to address the country's most preoccupying issue and ending up in a puzzle of contracts (Ferrario and Kanavos, 2015; Leopold et al., 2013). For instance, in Australia in 2015, among 98 contracts, some were outcome-based or financially based, some promoted evidence generation and others were hybrid, depending on the payer's priority (Lu et al., 2015). In the context of PM, usual financing through basic social insurance coverage can represent a challenge. Indeed, it is economically irrational for health insurers and other healthcare sponsors to cover PM without a clear idea of the clinical or cost-efficiency outcome. The above-mentioned contracts, hence, offer an alternative that should be seriously considered.

4.4.2 Discussion of Potential Solutions

Several authors discuss the variations in the cover for PM technologies and present possible solutions. For instance, Miller et al. (2011), Fugel et al. (2012) and Lu et al. (2018a) plead the creation of one central HTA agency will reduce differences between payers on the one hand and foster innovation on the other hand. This centralization of the cost- and clinical-efficiency assessment will facilitate the drugs' review and coverage guarantee. The HTA institution would be able to define a WTP threshold and emit recommendations regarding coverage, thus reducing the number of stakeholders taking part in the process. Vozikis et al. (2016) add that a single HTA agency could aid the government to tackle selected priority issues. As discussed in Section 4.3.2, a valid alternative is also to go further and standardize regulations regarding assessment and coverage of PM drugs at a larger, e.g., international, level. Nonetheless, as highlighted by Garfield (2011), Schwarzer et al. (2015) and Faulkner et al. (2016), the extension of a scheme for appraisal and coverage at an international level is cumbersome. Indeed, each country has its own infrastructure and healthcare system, which builds on the government's areas of priority in

health management and may not, or hardly fit other objectives decided at a larger scale.

The need for more transparent communication is also a recurring matter when dealing with PM, along with an alignment between the conflicting partakers, the manufacturers and payers. Trosman et al. (2011), Akhmetov and Bubnov (2017), Knowles et al. (2017) and Lu et al. (2018a) advocate that early and enhanced communication improves coverage. Early communication from the payers to the manufacturers about their requirements for evidence development will improve decision-making once the payers have the necessary data, reducing the need to create additional contracts. Further, information sharing among different payers would result in similar assessment schemes among payers. Thomas et al. (2010) assert that reimbursement systems should develop clearer standards. Coupled with communication, collaboration between stakeholders is the next step for further PM integration. Garfield (2011), in her assessment of European reimbursement systems for PM, concludes that "greater collaboration [...] should occur between the agencies involved in coverage and payment".

4.5 Implementation in the Healthcare System: Characteristics of PM

4.5.1 Description of the Challenges

The first hurdle payers encounter while deciding whether to cover PM is the clinical relevance of certain procedures. In her review of PM coverage, Degtiar (2017) finds that among private payers, tests are deemed "experimental" and "investigational". This observation is recurrent through the literature, especially for NGS. Indeed, sequencing lies at the frontier between medically necessary and experimental or investigational technology as its purpose is to simultaneously inspect several genetic mutations, however, in many cases, without a clear actionable outcome. Additionally, when another pathogenic mutation is found, unrelated to the primary diagnostic, this so-called incidental finding can lead to confirmatory testings. The question whether the following testings should be reimbursed is another issue payers must think through when deciding for NGS coverage. Overall, payers encounter difficulties in predicting costs as the presence of a mutation in an individual makes members of the family eligible for cascade testing, for example in the case of breast cancer screening (Amendola et al., 2019). This renders the final coverage decision difficult as mentioned by Trosman et al. (2018) and Trosman et al. (2015). The lack of cost predictability is one of the main reasons for coverage denial (Trosman et al., 2010; Deverka and Dreyfus, 2014; Messner et al., 2016). In the same vein, Lu et al. (2018a) assess coverage for multigene testing to confirm findings that the private payers not covering the tests regard them as experimental or investigational. According to Amendola et al. (2019) and Trosman et al. (2017), germline and hereditary cancer panels suffer from the same hardship in getting coverage. PM in general suffers from the same pragmatic issue, as seen in Meckley and Neumann (2010) and Hresko and Haga (2012).

The second hurdle is the high price of PM technology. By definition, PM drugs are targeted to small clusters of selected individuals. This spreads the costs of research and development on a narrower population (Thomas et al., 2010). Further, manufacturers producing drugs aimed at the treatment of rare diseases have high chances of becoming monopolists on specific markets. Such a setup typically comes with higher prices (Garrison and Austin, 2006; Pauly, 2019; Garrison and Towse, 2017; Degtiar, 2017). Concrete current examples are orphan drugs (Orofino et al., 2010; Schey et al., 2011; O'Sullivan et al., 2013). Several authors mention this characteristic of PM technologies as an additional obstacle to coverage. Degtiar (2017) emphasizes the increase in healthcare costs due to the increase in the number of orphan drugs on the market. The high price of personalized drugs and their impact on the total healthcare expenditure in the accounting period (e.g., the year) of the treatment is given. For PM drugs the time horizon for cost-efficiency studies needs to be different as such drugs often avoid the longer-term administration of other (cheaper) drugs.

4.5.2 Discussion of Potential Solutions

As healthcare evolves, the price and valuation of health technologies are to follow. Authors like Ramsey et al. (2006), Deverka (2009), Deverka and Dreyfus (2014), Carrera and IJzerman (2016) and Garrison and Towse (2017) mention the necessity to switch to a more comprehensive assessment of the value, the pricing and reimbursement of PM technologies. Kanavos and Angelis (2013), among others propose a framework for a value-based assessment of new medical technologies which could easily be applied to PM. They suggest that the so-called multiple criteria decision analysis (MCDA) should incorporate parameters related to "value creation" complementing the efficacy and effectiveness criteria of a technology. They have elaborated an MCDA tree for HTA that considers 12 criteria along four categories: the burden of illness, the therapeutic impact of the drug (which incorporates the efficacy and effectiveness parameters), the innovation level and the socioeconomic impact. Subsequently, weights are assigned to each criterion to compute scores for each option. This framework could be used to decide either for coverage or for price setting.

In view of the high prices at which the personalization of healthcare comes, it is necessary to seek the best financing schemes. The coverage of a drug, which could eradicate a health condition can be seen as an investment decision by the payer. However, under the current healthcare frameworks, the payer can sometimes not entirely capture the "benefits" of such investments in the following years (e.g., because the patient receiving the treatment quits the contract with the private insurer that has paid). A paper by Mattke et al. (2017) classifies multiple solutions to the issue insurers encounter when deciding to cover an expensive drug. Some could be applied to the case of PM. The authors propose multiyear contracts with possible compulsory applications in the case of gene therapies. A multiyear contract would bind the patient to the insurer that funded the cure. This enables the insurer to get the return of its investment in the following years, as benefits of a cure typically take longer than a year to emerge. In the

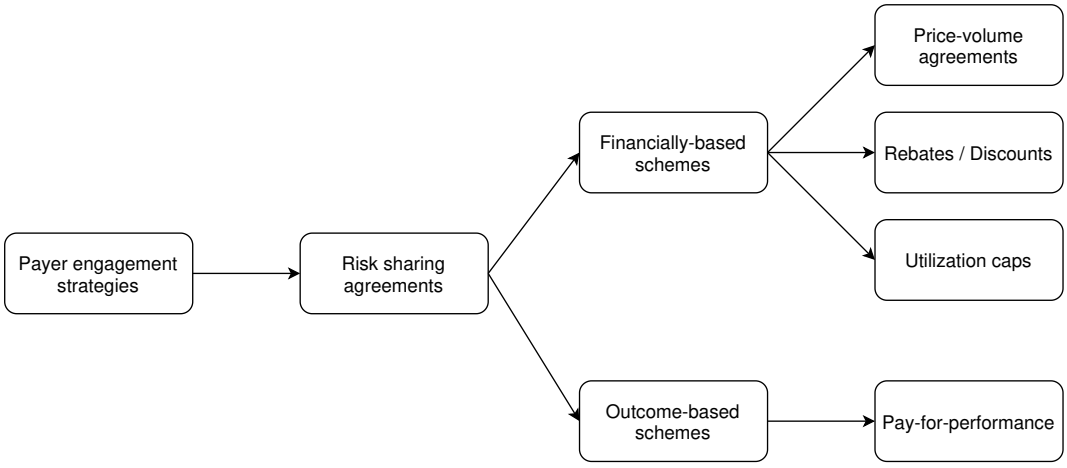

Figure 4.2: Examples of MEA schemes for cost mitigation based on Akhmetov and Bubnov (2017).

same vein, a "health currency" is proposed as a monetization of health (initially presented by Basu, 2015). The idea is that every investment in cures by public or private payers gives birth to "HealthCoins" that are transferable. When a patient later enrolls in a new health plan, the new insurer must buy out the health coins from the former payers. Thus, the insurer that invested in the cure will get partial reimbursement. This currency, hence, decreases the risk borne by the insurer. Other options include a cure fund or reinsurance for specific high-cost cures. Finally, the authors discuss government interventions such as patent buyout, – where the manufacturer will be compensated for its investments in innovation, – or tax coverage, – where the expensive drugs and technologies can be directly funded through tax revenues.

To reduce the financial risk borne by the payer, RSA (or so-called MEA or PAS) are being implemented. These contracts can serve several aims simultaneously, such as reducing the risk of outcome uncertainty, with the example of CEDs (cf. Section 3.2), and granting patient access for high-priced drugs (Ferrario and Kanavos, 2015; Lu et al., 2015; Faulkner et al., 2016; Akhmetov and Bubnov, 2017; Degtiar, 2017; Lu et al., 2018b). In Figure 4.2, based on the payer engagement strategies presented by Akhmetov and Bubnov (2017, Fig. 1), we lay out the schemes that primarily address the high cost of new drugs.

Price-volume agreements (PVA) define a threshold of total expenditure and when the predefined amount is topped a discount is triggered. These agreements fix prices at a maximum level for a specific volume (Ferrario and Kanavos, 2015). Faulkner et al. (2016) present the cases of France and Germany where this type of contract is implemented for high-cost medicine. Similar to PVAs, caps set a maximum time or dose amount for the treatment to be efficient, above which the manufacturer pays for additional treatment continuation. These agreements are currently used in the United Kingdom (and more specifically in England, see Garrison et al., 2013, and Faulkner et al., 2016). Other solely price-based agreements between the manufacturer and payer, also in place in the United Kingdom, are rebates or discounts (Ferrario and Kanavos, 2015). These agreements are purely economic and do not contain any outcome component. Another possibility for an institution to reduce the budget impact by high-priced drugs are traditional

co-payment or cost-sharing procedures (Garrison et al., 2013; Pauly, 2019; Degtiar, 2017). Under this setting, the patient financially participates to the costs for treatments, reducing the payer's participation (Faulkner et al., 2016). Finally, the presented pay-for-performance scheme in Figure4.2 allows for payers to pay the manufacturer only in the case of success. This success is designated by both parties as the achievement of an agreed outcome, which may be a positive health outcome or simply a limitation of negative events (Faulkner et al., 2016; Akhmetov and Bubnov, 2017).

Some of the above arrangements are already in place for non-PM technologies (Garrison et al., 2013; Ferrario and Kanavos, 2015; Lu et al., 2015; Faulkner et al., 2016). Such methods could be successfully applied to PM to address the raised issues. Some of these contracts can be combined to address multiple barriers simultaneously, as seen for example in Australia (see Lu et al., 2015).

Finally, other types of cost-retaining strategies can be applied. Leopold et al. (2013) report the case of trastuzumab, a personalized drug for HER-2 positive breast cancer patients, in Latvia. While the diagnostic test is reimbursed for all breast cancer patients, the treatment is subject to assessment. Due to a limited budget, the reimbursement of the treatment is analyzed on a case-by-case study, thus reducing expenses to only positive and deemed necessary cases. In the latter procedure, other non-economic questions arise, notably the decision on "necessity" in each case relating to ethical issues and the valuation of QALYs.

4.6 Concluding Discussion

In our review of the PM literature and our assessment of the building blocks of PM from a payer's perspective, we reveal three major impediments for integrating PM in healthcare systems. The hardship comes from different areas: economic relevance, governance and practical implementation of PM in the healthcare system. Solutions are available but need to be properly put into practice. A common approach lies in the collaboration among partakers. Collaboration between manufacturers and institutional payers like a national social health insurance scheme or a private insurer will more easily and rapidly generate the necessary base of evidence for drug coverage. Cross-border collaborations between HTA agencies and payers would help achieve standard thresholds for the coverage of treatments. Finally, a close collaboration among the various payers themselves is necessary to provide unified coverage by sharing and harmonizing data.

In the building of the new paradigm, the implication of each stakeholder is necessary to ensure the financial management of PM. In particular, the payers and manufacturers are the enablers of the next phase of evolution toward an individualized medicine. On the one hand, payers are asked to take a leap of faith in contributing to evidence generation by covering PM drugs blindfolded on its real-world cost-efficiency. To secure the jump, manufacturers, governments and HTA bodies must establish guidelines and a standard procedure for PM technologies to be quickly assessed. On the other hand, the appraisal of coverage based on the calculation of

pure economic costs should include the value created, e.g., in terms of QALYs, by the use of personalized treatments. Finally, with the new outlook on healthcare, and especially with the necessity to at first invest in a system which may not yet be proven economically rational, health should be regarded as an investment on the long term rather than a cost on the short term.

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Appendix

The following table provides a comprehensive overview of the 52 reviewed papers.

Synopsis of reviewed papers.

Reference	Region	Methodology	Key contents and main results	ER	GC	HS
Akhmetov and Bubnov (2017)	US	Survey/interviews ($N = 75$)	– Manufacturers may benefit from accessing claims data – Collaboration and trust are key, data exchange improves evidence paucity – Early dialogue between producers and payers enables better integration	✓	✓	✓
Amendola et al. (2019)	US	Review of coverage ($N = 31$)	– Guidelines not meaningfully identify patients who may benefit from testing – Germline cancer test often deemed experimental or not medically necessary – Difference in denial because difference in evidence assessment	✓		✓
Basu (2015)		Conceptual article	– HealthCoins to address the "free-rider" problem among insurers – HealthCoins to enable smooth investments across insurers – HealthCoins are produced with investments and bought out by next insurer			✓
Boon et al. (2015)	NL	Discussion	– None of 46 orphan drugs on conditional reimbursement were de-listed – De-listing solely on cost-effectiveness faces social pressure – Four years re-evaluation for quality evidence production is too short	✓	✓	
Carrera and IJzerman (2016)		Discussion	– PM drugs are particularly costly due to narrower customer base – Stakeholders have different WTP thresholds per QALY – MCDA incorporates in HTA the multidimensional value of PM			✓
Chalkidou and Rawlins (2011)		Discussion & case studies	– Discussion of interrelated impact between CED and pharmacogenetics – CED contracts offer an alternative solution for public reimbursement – Healthcare system has to be adjusted for optimal RSA implementation	✓		
Cohen et al. (2013)	US	Review of reimbursement ($N = 8$ PGx)	– Lack of comprehensive reimbursement of CDx and high costs of PGx – Often low evidence of clinical usefulness – Payers report that tests cost for everyone but help only a few	✓		
Cohen and Felix (2014)	US	Review (10 drug-diagnostics) and survey ($N = 11$)	– Variable and relatively high patient co-insurance – Drug reimbursement is not necessarily coupled with diagnostic coverage – Need to increase the body of evidence ; CED to increase data	✓		
Degtiar (2017)	42 countries	Literature review ($N = 69$ articles)	– Private payers deem tests investigational and cover them less – Value-based assessment for reimbursement to incorporate other criteria – Need for evidence guidelines from payers	✓	✓	✓
Deverka et al. (2007)	US	Survey/interviews ($N = 60$)	– Lack of clinical utility as a barrier for molecular medicine coverage – Public-private partnership for effectiveness research data generation – Establishment of accurate regulation to avoid uncertainty	✓		

Synopsis of reviewed papers *(continued)*.

Reference	Region	Methodology	Key contents and main results	ER	GC	HS
Deverka and Dreyfus (2014)		Review of NGS coverage	– Lack of clinical utility information and standards – Move reimbursement from a cost-based to a value-based approach – Payers concerned with reimbursement of confirmation of incidental findings			✓
Deverka (2009)		Commentary	– Payers have evidence requirements more rigorous than regulators – Coverage assessment needs positive net benefit as compared to usual care – Opportunity for informed decision-making by linking payer information	✓	✓	✓
Faulkner et al. (2012)	US	Review	– Research prioritization and early standardized value assessment – Best practice for clinical evidence development / health economic assessment – New incentive and reimbursement approaches for PM	✓		
Faulkner et al. (2016)	EU & US	Review of pricing and reimbursement	– Earlier cross-stakeholder engagement and regulatory tools – Flexible and adaptive payer approaches to pricing and reimbursement – Iterative evidence generation and specific funding		✓	✓
Ferrario and Kanavos (2015)	BE, UK, NL, SE	Review of MEA ($N = 133$)	– Conceptual framework for MEA agreements and tests – Different types of agreement and medicine-indications across countries – Variation from governance and risk-perception	✓	✓	✓
Fugel et al. (2012)	EU & US	Review of pricing and reimbursement	– Lack of a consistent process for value assessment of more complex diagnostics – More flexible pricing & reimbursement systems are needed – Further development of framework for access of diagnostic-based therapies	✓	✓	
Garfield (2011)	10 EU countries	Review of reimbursement	– European reimbursement systems are not appropriately aligned – Change health technology assessment methodologies – Need for integrated reimbursement pathways and drug coding systems	✓	✓	
Garrison and Austin (2006)		Commentary	– Limitations of genetic prediction and lack of economic incentives slows PM – Clinical successes often on a case-by-case basis – Develop strong intellectual property and value-based, flexible pricing systems			✓
Garrison and Towse (2017)		Concepts for pricing and reimbursement	– Take an economic perspective and a broader concept of value – Valuations beyond QALY including changing preferences over life – Inflexible or cost-based reimbursement systems as barriers for PM			✓
Garrison et al. (2013)		Review of RSA ($N = 116$)	– Performance-based risk-sharing arrangements to reduce uncertainty – Practical recommendations for state-of-the-art methods – Data regulation and long-run societal perspective needed	✓		✓

Synopsis of reviewed papers *(continued)*.

Reference	Region	Methodology	Key contents and main results	ER	GC	HS
Graf et al. (2013)	US	Review of coverage ($N = 206$ policies)	– Half of insurers do not cover specific genetic-related services – One-third of the insurers addressed genetic testing – Challenges in ensuring consistency and homogeneity among insurers	✓		
Hall and McCabe (2013)		Commentary	– Cost-effectiveness standards are more poorly defined for PM – Regulation of diagnostic tests less rigorous – Harmonize methods and increase modelling transparency	✓		
Hresko and Haga (2012)	US	Review of coverage ($N = 41$ policies)	– Lack of evidence of clinical utility as a barrier for coverage – Variable coverage determinations and factors considered – Inclusion of PGx information in drug package inserts seems relevant	✓	✓	✓
Kanavos and Angelis (2013)		Concept for value assessment	– Multiple criteria decision analysis: HTA for broader value inclusion – Values: illness burden, innovation, therapeutic and socioeconomic impact – Score: weights are assigned according to an institution's priorities			✓
Knowles et al. (2017)		Literature review ($N = 344$ articles)	– Science of PM requires broadening beyond genetics – Lack of clinical uptake due to structural and human factors – Recommendations on financial and regulatory barriers to be addressed	✓	✓	
Leopold et al. (2013)	27 EU countries	Survey ($N = 27$)	– In the EU four broad models for PM funding (case study trastuzumab) – Most EU countries: combined hospital and 3rd party payer strategy – No combined funding for diagnostic test and medical treatment		✓	✓
Lu et al. (2018a)	US	Review of coverage ($N = 18$ payers)	– Important variation among guidelines, especially in private payers – A second HTA agency assessment could reduce coverage variation – Increased dialogue and sharing prior information to reduce coverage variation	✓	✓	✓
Lu et al. (2015)	Asia-Pacific countries	Literature review	– Most PAS focus on pharmaceuticals, few on medical technologies – Majority involve pricing arrangements, evidence generation rarely used – Australia has strong experience with PAS	✓	✓	✓
Lu et al. (2018b)		Commentary	– Clinical utility unanswered for many genomic technologies – Propose building blocks for rapid generation of evidence – Proven analytical and clinical validity needed, collaborative models for action	✓		✓
Mattke et al. (2017)		Discussion	– Policy options to remedy the "free-rider problem with high-cost cures – Incentives for patients, coordination among payers, government intervention – Collaborations for equitable mechanisms for cost-benefits distribution			✓

Synopsis of reviewed papers *(continued)*.

Reference	Region	Methodology	Key contents and main results	ER	GC	HS
McCabe et al. (2008)	UK	Commentary	– NICE is the only entity to assesses effectiveness and cost-effectiveness – Cost-effectiveness threshold of NICE is £20 000 per QALY – Threshold should be regularly reevaluated to match budget and innovation	✓		
Meckley and Neumann (2010)	US	Case studies of diagnostics and treatments ($N = 6$)	– Strength of evidence is the strongest predictor for drug reimbursement – Regulatory oversight and cost-effectiveness not associated to reimbursement – Absence of coverage triggers direct-to-consumer marketing	✓		✓
Merlin et al. (2013)	Australia	Review of reimbursement	– Safety, effectiveness, and cost-effectiveness for reimbursement decisions – Linkage of different types of evidence and likely clinical benefits of drugs – Framework allows to merge different data sources to increase the database	✓		
Messner et al. (2016)	US	Policy Delphi panel ($N = 48$)	– Proprietary variant databases are a key challenge for NGS coverage – Payer policies and perceived inconsistency in standards as a barrier – FDA regulation not strongly perceived as a barrier	✓	✓	✓
Miller et al. (2011)	EU	Market study	– Insufficient clarity on reimbursement and regulatory pathways for PM tests – Value-based public sector pricing required in Europe – EU market suffers from decentralization	✓	✓	
Pauly (2019)		Review of coverage	– Study on patterns of insurance coverage for PM and efficiency – Heterogeneity in marginal benefits call for partial coverage – Case studies: tests providing more benefits than costs should be fully covered			✓
Payne and Annemans (2013)	EU	Literature review	– Successful market access driven by generation of robust evidence – Take account of the different stakeholders' perspectives – Suggestion of possible approaches and necessary timescales	✓	✓	
Phillips et al. (2017)	US	Review of coverage ($N = 55$ policies)	– Multigene tests do not fit standard coverage framework – High degree of variability in coverage assessment for multigene tests – Payers deny coverage because of lack of evidence and actionability	✓		
Ramsey et al. (2006)		Commentary	– Currently, reimbursement is based on the price rather than clinical value – Reimbursement to move to an evidence- and value-based paradigm – Standardize presentation and filling information gap benefits all			✓

Synopsis of reviewed papers *(continued)*.

Reference	Region	Methodology	Key contents and main results	ER	GC	HS
Schwarzer et al. (2015)	11 countries	Review of thresholds	– Explicit cost-effectiveness thresholds only in two countries (UK & TH) – Implicit values in other countries and diffrent decision-making rules – No PM-specific threshold found		✓	
Simeonidis et al. (2019)		Literature review ($N = 96$ articles)	– Outcome of interventions mostly measured in QALYs – Total cost estimated upon direct medical cost data – Need for cost-utility analyses within national healthcare systems	✓	✓	
Sullivan et al. (2011)	High-income countries	Review of cancer care delivery	– Clinicians require analytic and clinical validity before testing – Coverage with evidence development is an opportunity to generate data – Alternative business models to be developed and encouraged	✓		
Terkola et al. (2017)		Commentary	– Lack of real-world data regarding costs and health outcomes – No study confronting clinical trial and real-world data – International coordination between regulators to establish standards	✓		
Thomas et al. (2010)	US	Industry perspective	– Need for reimbursement that fosters evidence development – Reimbursement systems should develop clearer standards – Regulatory process has to integrate CDx in the appraisal of the drug	✓	✓	✓
Towse and Garrison (2013)		Commentary	– Collaboration between stakeholders needed to increase evidence creation – CED for realistic expectations for evidence standards – Public investment along with manufacturers and payers to generate data	✓		
Trosman et al. (2010)	US	Interviews ($N = 7$)	– Heterogeneity in clinical evidence perception among payers – Clinical effectiveness is a paramount factor in coverage decision for all payers – Approach to consider both clinical evidence and health care system factors		✓	✓
Trosman et al. (2011)	US	Literature review and interviews ($N = 11$)	– Payers use HTA more extensively for PM than for other technologies – Limited relevance if HTA unavailable and insufficient nonclinical factors – HTA organizations to improve their relevance to payers and clinicians		✓	
Trosman et al. (2015)	US	Interviews ($N = 24$ experts / payers)	– Next-generation tumor sequencing deemed experimental/investigational – Efforts for evidence generation and incorporation into policies necessary – Misalignment between evidentiary methods and payers' needs			✓
Trosman et al. (2017)	US	Interviews ($N = 11$ payers)	– Adjustment needed for PM to fit the coverage framework – All interviewees find that lack of evidence is a coverage barrier – Manufacturers need to include payers' evidentiary requirements			✓

Synopsis of reviewed papers *(continued)*.

Reference	Region	Methodology	Key contents and main results	ER	GC	HS
Trosman et al. (2018)	US	Review of coverage	– Three approaches to adapt coverage framework for tumor sequencing – RSA with manufacturer for performance data; CED for evidence generation – Technology-specific coverage based on number of genes			✓
Vegter et al. (2008)		Literature review ($N = 20$ articles)	– Level of consistency among economic analyses generally poor – Extensive sensitivity analyses and incorporate evidence-based data – Checklist for performing pharmacoeconomic analysis	✓		
Vozikis et al. (2016)	EU	Review of pricing and reimbursement	– Overview of basic principles guiding governance of genomic testing services – Need for one single HTA agency for selection of priority areas – Merge all the current reimbursement processes under one committee	✓	✓	

Note: **ER** = Economic relevance, **GC** = Governance challenges, **HS** = Implementation in the health care system

Chapter 5

Personalized Health Survey Description and Statistics

Abstract: In this chapter, after a brief presentation of the survey conducted in March 2020 on the topic of personalized medicine, with a focus on genetic tests in a preventive setting. For the purpose of this research, we provide some insights based on descriptive statistics. The survey includes Swiss residents, evenly distributed among gender (50%/50%), age (between 25 and 65 years old) and region of residence (67% German-speaking and 33% French-speaking). The first set of variables under study are reasons or barriers to usage of health apps or wearable devices that collect health data and data from blood or genetic tests. From the sample's statistics, we highlight that the major reason to use these PM technologies is prevention (50.6% for apps and wearables and 62.4% for blood or genetic tests). Concerns with data protection are an obstacle for roughly 55% for both apps and blood and genetic tests. Regarding actors with which individuals are ready to share anonymized data hence collected, the top three is composed of the doctor (with up to 80% willingness to share for blood or genetic anonymized data), followed by family and friends and at the third place are university researchers (45.3% for apps and 40% for blood and genetic tests). Health insurers are the fourth actor, with whom 31.4% of the sample agreed to share anonymized genetic data. Finally, an analysis of other variables allows us to grasp public sentiment towards genetic testing. Overall, the sentiment is rather positive, a majority of individuals associate genetic testing with positive outcomes such as an increase in life expectancy and rarely with negative potiential aspects like discrimination of disabled people. Cost of genetic testing being too high, is on the other hand, a tangible fear for 55.5% of the individuals. Finally, for insurance-related considerations, 36.6% of the sample believe it will be more difficult for their family members to underwrite an insurance contract where 33.1% disagree with the statement.

5.1 Survey setup

In this chapter, we present, along with some additional descriptive statistics, the original survey that was conducted in March 2020 in Switzerland for the purpose of our study. Before releasing the survey, we have submitted several versions of if for testing with our colleagues, friends, and family. The aim was to collect their potential feedback and ensure that all the questions were understood correctly. In the adverse case, the questions were rephrased and resubmitted. The sample poll was made of 25 to 30 individuals with various backgrounds. Subsequently, the collection of the data was conducted by a professional polling agency complying with our selection criteria regarding the sample. Our sample comprises 1 000 respondents with the following characteristics: evenly distributed by gender (50% each), by age along four categories spanning 10 years between 25 and 65 years (25% each) and two thirds of the sample coming from the German-speaking regions of Switzerland, with the other third coming from the French-speaking regions. The main focus of this survey is PM, the willingness to use its technologies under different settings and the sentiments associated. A set of socioeconomic questions were added to present a complete analysis and view of the individual. The survey is composed of 39 questions dealing with selected aspects of genetic testing. The complete list of questions is available in the Appendix. The design of the survey is original as it allows for the integration of several dimensions into our analysis by the usage of framings. In chapters 6 and 7, we dive into the effect of these framings defined by a change in the payer of genetic tests (see Figure 6.1) and in the structure of usage and storage of the health data collected by wearable devices or direct-to-consumer genetic tests (see Figure 7.1), respectively.

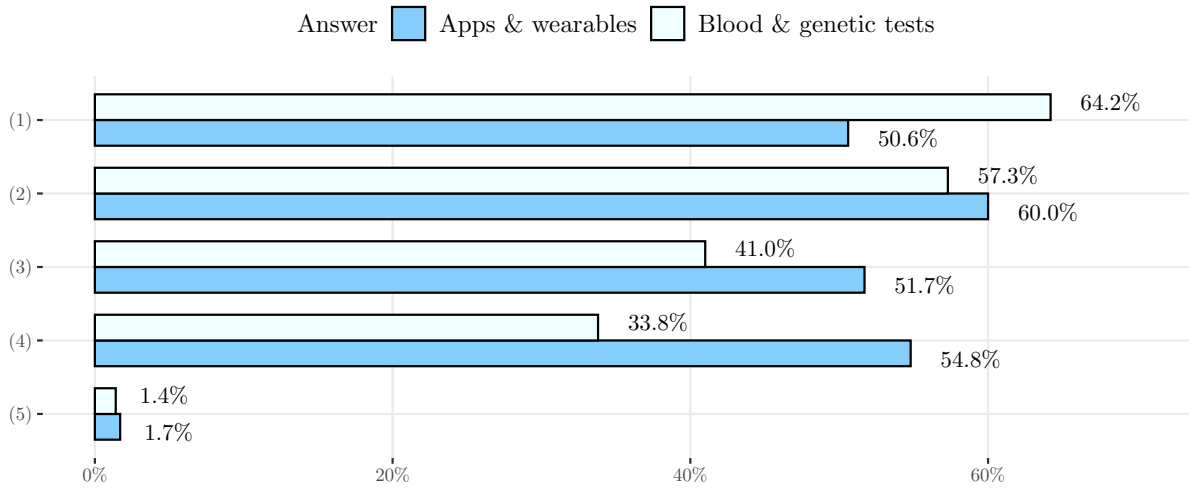
5.2 Descriptive statistics

5.2.1 Apps, wearable devices, blood and genetic tests

In this section, we take a look at the statistics of our sample to have a picture of individuals' approach to PM. The first question of our survey concerns apps on smartphones and wearable devices to collect the daily step count, exercise tracking or sleep cycle. Of the interrogated individuals, 70.2% ticked that they are using or would probably use them. This level of agreement drops at 49.7% when it comes to blood or genetic tests to determine food intolerances, create an exercise plan or evaluate the risks of a hereditary disease for instance. The difference in usage between the two technologies is of 20.5 percentage points. Subsequently, depending on the answer to questions 1 and 2, we inquired the individuls for the reasons for their refusal or agreement as presented in Figure 5.1 and Figure 5.2, respectively. Several answers could be selected. Some possible answers are inspired from a study conducted by Gröninger and Lacher (2017). For instance, the usage of apps for health state surveillance or prevention.

For the first reason, our sample agrees at 62% that they are using or will be willing to use

blood or genetic tests for prevention. Interestingly, this reason is valid only for 51% of apps and wearable devices users. Curiosity, on the other side, pushes more individuals to install health apps and wear recording devices than undergoing tests, at 60% vs. 57%, however, still being the main reason for compliance. These results are aligned with the literature, where in Kauffman et al. (2017), 69% of the interviewed stated that curiosity is a strong incentive to undergo genetic testing. Curiosity being the drive, in a 2021 report by Apptentive, the average retention rate of 90 days on health apps is of 34%.[1]. To retain the user on the health apps and reap the associated benefits, the creators employ several behavioral techniques. Such techniques range from goal-setting or scheduling for non-gamification-like ones behaviors to gamification like via rewards or progress feedback (Edwards et al., 2016; Cheng et al., 2019). Finally, surveillance and sport or health coaching take the third and fourth place for tests, with fewer agreements than for apps and wearables. In a study conducted by Gröninger and Lacher (2017) on health data, among the 418 surveyed, half said recording health data. Among the chosen reasons, 50% agreed doing so for sport coaching, 46% out of curiosity, 36% for health surveillance and only 11% for prevention. While other results are close to ours, prevention does not seem to trigger individuals as much as it does in our sample. This could be explained by the relatively young sample, with 61% of surveyed individuals between 20 and 34 years old versus 25% in our case. Thus, prevention and health monitoring are not the driving rationales.



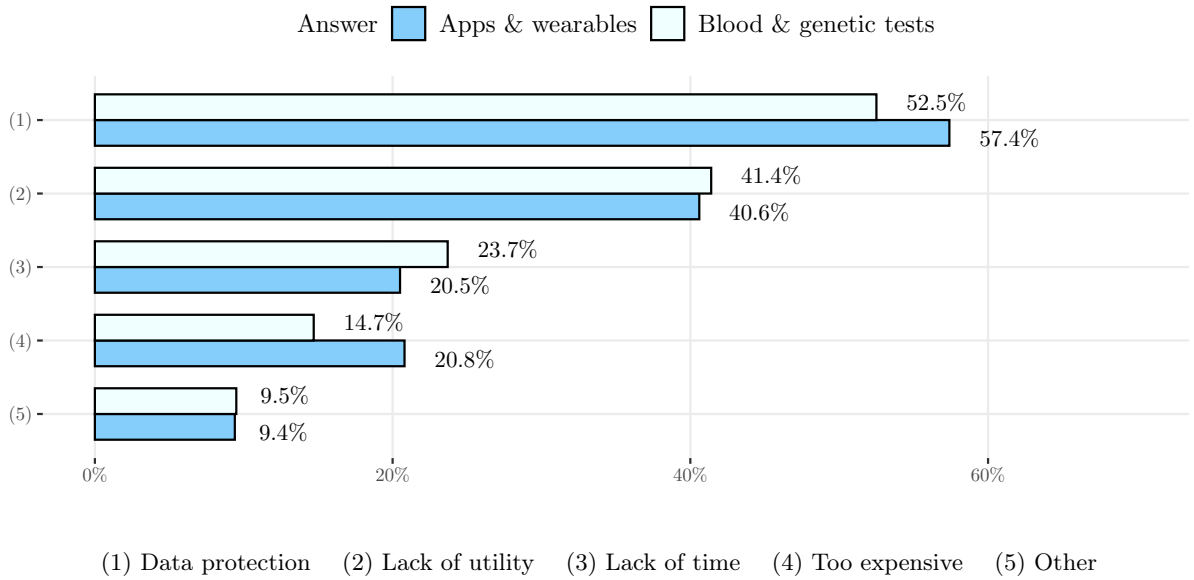
(1) Prevention (2) Curiosity (3) Surveillance (4) Coaching sport / health (5) Other

Figure 5.1: Reasons for accepting usage

For those stating that they probably or very probably would not use blood or genetic tests, 53% indicated having fears regarding data protection, making it the primary reason of refusal for usage of these technologies. This fear is even more present among interviewees regarding refusal for app and wearable devices use, with 58% agreement. In our survey, lack of utility was ranked second with 48% of agreement for 41% for both apps and tests in our sample and the lack of

[1]https://www.apptentive.com/2021-benchmark-report/

time discouraged on average 22% for apps and tests. These possibilities are inspired from an online survey conducted by Gröninger and Lacher (2017), we can hence compare our results. In Gröninger and Lacher (2017), the lack of utility and of time were ranked first and second with 48% and 32%. Finally, 24% admitted prices too high as being a reason. In a similar survey among approximately 1'700 individuals, Allain et al. (2012) found that prices being too high deterred 28.8% of respondents from doing a genetic test.



(1) Data protection (2) Lack of utility (3) Lack of time (4) Too expensive (5) Other

Figure 5.2: Reasons for refusing usage

In the next question, we listed a few actors with whom the individual may want to share anonymized data and obtained the ranking in Table 5.1. Multiple responses could be selected, the most relevant actors such as the doctor, scientific researchers or family and friends were taken from Haga et al. (2013). Unsurprisingly, individuals are the most likely to share their data with their doctor with a probability of 80%. The next actors are family and friends with a drop to 46%, closely followed by university researchers with 40% of frequency of agreement. The least likely groups to receive data are the employer with a propensity to share of 8% and social media with 7%. The low willingness to share this sensitive type of data with the employer could be explained by individuals' fear of discrimination. In a survey performed by Allain et al. (2012), 28.6% of interviewees are afraid of genetic discrimination by the employer. Regarding the insurer, in Dalpe et al. (2017), 87.5% of women think that their breast cancer test results would negatively impact their or relative's capacity to obtain personal insurance. For another few examples, Haga et al. (2013) and Hall et al. (2005) found that 51% of the former and 40% of the latter's surveyed individuals agreed that it will be more difficult to get insurance or a job. The same mechanism could operate for social media, explaining the similar

low percentage of share. Interestingly, such a pattern is also visible in a survey conducted by the Sotomo Institute and Fondation Sanitas. The study by Bühler et al. (2019) interrogated a panel of 2'074 representative individuals about their readiness to share recorded health data (e.g. steps count, menstrual cycle, sleep pattern) with several actors, among which their personal doctor or health researchers. The figures are very similar to our results concerning willingness to share blood or genetic data, with a 81% devoted to the personal doctor and 42% to health researchers.

Agent	Apps & wearables	Blood & genetic tests	Δ
Doctor	75.1%	80.0%	+4.9 pp
Family & friends	62.2%	46.4%	−15.8 pp
University researchers	45.3%	40.0%	−5.3 pp
Health insurer	31.4%	23.6%	−7.8 pp
State datasafe	27.9%	23.1%	−4.8 pp
Patients network	26.7%	20.2%	−6.5 pp
Pharmaceutical companies	21.8%	15.5%	−6.3 pp
Technological companies	22.1%	8.6%	−13.5 pp
Employer	13.3%	7.6%	−5.7 pp
Social media	16.5%	7.0%	−9.5 pp

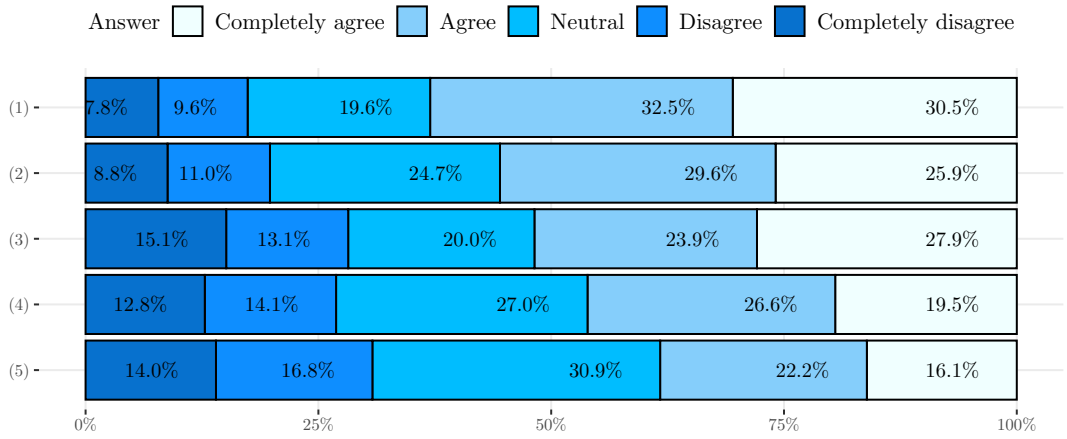
Table 5.1: Willingness to share anonymized data

5.2.2 Genetic tests

Several questions in our survey focus on genetic tests. To ensure a common understanding of the purpose of genetic tests in the context of our survey and PM, we displayed the following paragraph: *For the following questions, we focus on genetic tests. Some of these tests determine the risk for hereditary diseases, for instance breast cancer for women and prostate cancer for men. These tests can then be used to plan the frequency of preventive medical examinations (e.g. mammograms) or to improve lifestyle (diet, physical activity) in order to decrease or postpone the development of the disease.* We then inquire individuals whether they are using or would be willing to use such a technology as well as the factors that could incentivize or refrain them from performing such a test. For all claims, individuals had to express whether they agree or disagree with a statement on a five-level Likert scale (Likert, 1932).

In Figure 5.3 we display the share of the five original possible levels of agreement to the incentives presented in the question. The levels range from "completely disagree" on the left to "completely agree" on the right, additionally, the lighter color indicates higher agreement levels. The incentives are ranked by percentage of agreement i.e., the sum of the "agree" and "com-

pletely agree" levels. Several incentives were taken from Bunn et al. (2002) as they proved to be relevant incentives to undergo genetic test in their sample. We hence as well wanted to capture some incentives such as the fact that genetic test results could help family and relatives to take better care of their health or incentivize then to undergo a genetic test themselves. The first incentive gathering the highest level of agreement (63%) is the will to have information about own hereditary disease or cancer risks. The same potential incentive has been submitted to a group of 964 individuals in a study by Henneman et al. (2013) where it gathered 44% of agreement. The second reason that can push individuals to undergo genetic testing is to better care of their health, i.e., prevention. This incentive works for 55.5% of our sample. If we compare these figures to the ones that can be found in literature, for instance, in Kauffman et al. (2017), 69% of individuals marked general information as a motivator to receive genetic sequencing. In a similar study by Lerner et al. (2017), 56.4% of the surveyed individuals rated the reason to undergo genetic testing "Inform the selection of effective disease prevention" as either very or extremely valuable. Going back to the study by Henneman et al. (2013), the percentage of agreement is very close to ours and the one in the literature, i.e., 53%. The third stimulus is simple curiosity about genetic makeup and is a good reason enough to do genetic testing for 51.8% of our sample. The last two arguments could be classified as altruistic as they take into account relatives, nonetheless, they do not exceed 50% of agreement, being rather a motive for a minority of people.



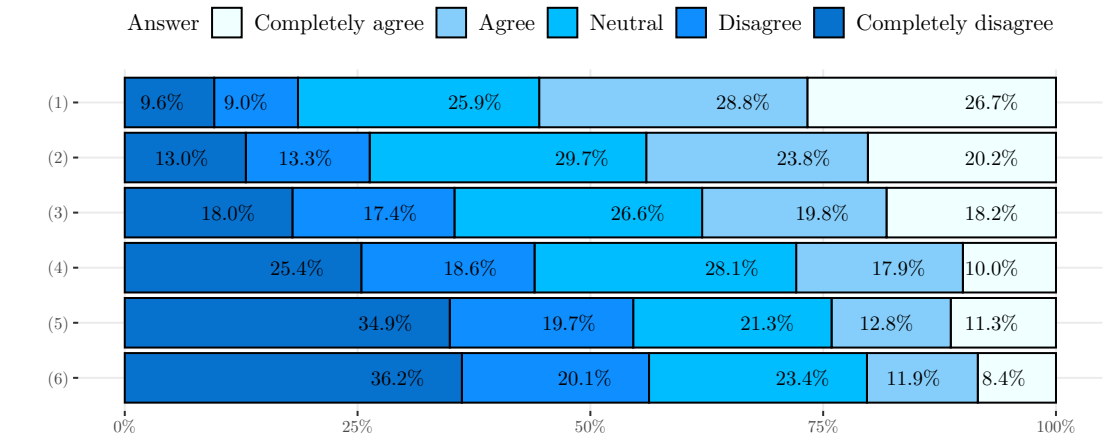
(1) Information about hereditary disease or cancer risks
(2) Take better care of health
(3) Curiosity about genetic makeup
(4) Help relatives take care of their health
(5) Incentivize relatives to undergo genetic testing

Figure 5.3: Incentives to undergo genetic testing

In Figure 5.4 we provide a closer look at the second category of factors in the decision for genetic testing: barriers. Similarly to the incentives, some possible hurdles proved to be relevant in Bunn et al. (2002), we hence took inspiration from them. They are ranked following the same scheme as the previous figure. Interestingly, contrary to what the literature would suggest, individuals are less concerned by discrimination than the monetary aspects of genetic testing. The cost of genetic testing as well as the possible impact on family finances following the results, are ranked as the first and fourth hurdle with 55.5% and 27.9% of agreement, respectively. The fear of discrimination, however, is a concern for only 24.1% of the sample. To put these figures in perspective, we can have a look at several studies which mention potential obstacles to genetic testing. For instance, Strobel et al. (2013) found that in their sample, 35% of individuals fear health insurance discrimination and 21% employment discrimination. In a more recent study by Dalpe et al. (2017), the authors found that 85% of women from 35 to 55 years old feared that test results will negatively impact their ability to obtain health insurance. As can be seen from the literature, concern about the cost does not appear as often as discrimination concerns. Regarding the incentives (2) and (3), the statistics for our sample are pretty similar to the ones of Henneman et al. (2013). We obtain 44% of agreement for the proposition that genetic testing has an impact on life decisions of individuals versus 36% for Henneman et al. (2013), and 38% for the reticence to get genetic information versus 45%. To be noted that as described in the survey, the aim of the genetic testing is mostly preventative. The individual would receive a risk-o-gram with the potential probability of developing a certain health condition. The results of these genetic tests are not as precise as in the case of sequencing for treatment. They are hence to be interpreted with care, which may explain why some individuals would rather not receive this information. The mean of delivery and the consequences on the lives of the patients receiving genetic testing information represents a real challenge in the clinical application of such technology (see, e.g., Ensenauer et al., 2005). To conclude the analysis, it is interesting to note that the fear of discrimination has the second highest level of complete disagreement (34.9%).

As a general observation, the surveyed individuals of our sample seem to have quite a positive outlook on genetic testing as incentives motivate more individuals to undergo genetic testing than barriers deter them. As a matter of fact, the top three incentives are true for more than 50% of the sample, compared to only one barrier.

The third and last category of sentiment-related questions inquires on the impact of genetic tests on society. The propositions are displayed in Figure 5.5 with the same levels as in the two precedent figures. Several expected consequences of genetic testing of society were extracted from Haga et al. (2013) where they proved to be relevant. A first observation one can make

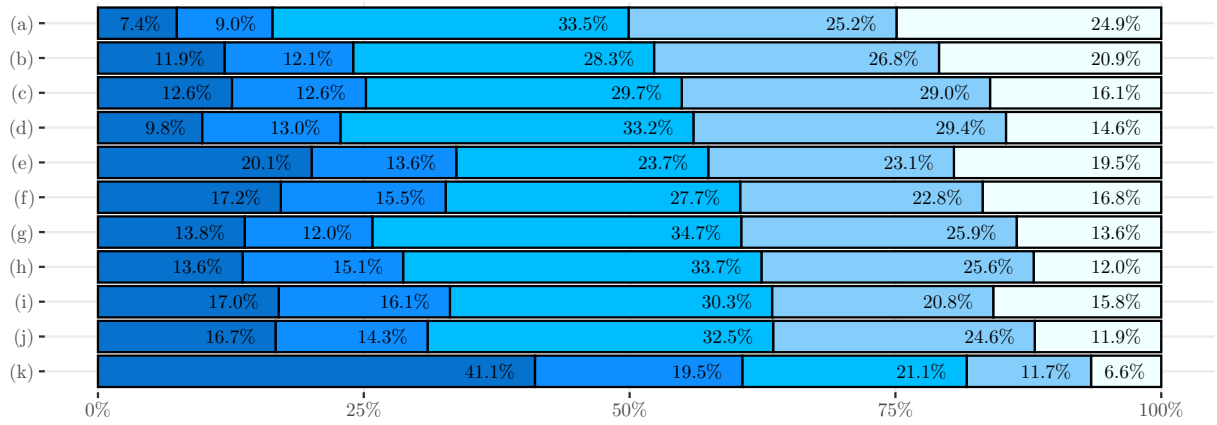


(1) Fear test too expensive
(2) Force to change lifestyle
(3) I do not want the info
(4) Impact on finances
(5) Fear of discrimination
(6) Family will disapprove

Figure 5.4: Barriers to undergo genetic testing

is the fact that the most frequent position in all questions except the last, is the neutral one. As a second observation, we notice that only the first proposition gathers more than 50% of agreement – that the government will not be able to protect from negative aspects of genetic testing. For the second possible impact of genetic tests on society, individuals seem to admit that there will be a segregation between "good" and "bad" genomes. It is interesting to note that in our sample, individuals are more pessimistic compared to a study conducted in 2010 on a sample of 964 individuals by Henneman et al. (2013). Indeed, our sample displays 47.7% of agreement about possible discrimination against 38% in Henneman et al. (2013). Similarly, only 45.1% of our sample believe that genetic tests will lead to fewer illnesses and longer life, compared to 64% in 2010. Regarding sequencing prior to premium establishment for insurance, 42.6% think that this will indeed be the case versus 36% in 2010. Finally, the two samples align on the last question – that genetic tests will be mandatory to be hired. Around 20% of agreement in both groups (18.3% in our sample vs. 21% in Henneman et al., 2013).

To conclude this overview, we are going to look closer at the answers of two insurance-related questions. For both claims, individuals had to chose a level of agreement on a five-level Likert scale. We merged the two extreme answers on both sides and as can be seen in Table 5.2, they are almost evenly distributed. For both assertions, the biggest categories are those with people agreeing that genetic testing will have a negative impact on the easiness to obtain an insurance contract and that insurance companies will ask for DNA sequencing prior to the establishment



(a) Government will not be able to protect from negative aspects
(b) Segragation between "good" and "bad" genomes
(c) Fewer illnesses and longer life expectancy
(d) All fœtuses will undergo genetic testing
(e) Sequencing prior to premium establishment
(f) Discrimination of disabled people
(g) All infants will have their genome sequenced
(h) Genetic test will be common
(i) More difficult for family to get insurance
(j) Everyone will have a genetic passport
(k) To be employed genetic testing will be necessary

Figure 5.5: Impact of genetic testing on society

of a premium.

	Disagree	Neutral	Agree
It will be more difficult for members of my family to underwrite an insurance contract.	331	301	366
Insurance companies will ask for a DNA sequencing to establish a premium.	337	237	426

Table 5.2: Genetic tests impact position

Both fears go hand in hand and have also been reported in several studies. In a population-based study of 622 adults, Bosompra et al. (2000) noted in their sample that 63.5% agree that if the genetic test reveals a high cancer risk, family members might have trouble getting coverage by health insurance companies. Few years later, in a survey conducted by Hall et al. (2005), among more than 85'000 adults in five primary-care field centers, 40% of respondents agreed that "Genetic testing is not a good idea because you might have trouble getting or keeping your

insurance" – an observation which is relatively close to the 36.6% of agreement in our sample. Finally, in a similar survey ran by Allain et al. (2012), the authors found that 19.5% of interviewees were anxious about insurance discrimination. We can hence reiterate our observation that the population surveyed for the purpose of our study has a general positive outlook regarding genetic testing and its consequences on society.

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Chapter 6

Determinants and the role of the payers in the uptake of genetic testing and data sharing in personalized health

Abstract: Using novel data from an ad hoc survey carried out in Switzerland, we determine the factors influencing the uptake and sharing of data from genetic tests. Through regression analyses, we use five sets of variables: socio-economic, lifestyle, health insurance, sentiment and political beliefs and two framings. The two framings assess the willingness to undertake the test and the readiness to share results of the test with the insurer when the costs of the tests are either borne by the insurer or by the individuals. We find that socio-economic, lifestyle or political belief variables have very little or no influence on the uptake of genetic tests and the sharing of the results with an insurer. On the contrary, our results indicate that sentiment and insurance factors play a strong role on the uptake and sharing. More precisely, if genetic tests are perceived as a mean to perform health prevention, this pushes individuals to uptake them by an increase in propensity of 10.9%. Further, using the insurer's smartphone app leads to an increase of 16.5% in the likelihood to undergo a genetic test and of 27.6% to anonymously share the related data with the insurer. Regarding insurance plans and deductible levels, there is no strong correlation neither with the willingness to uptake the test, nor to share the data. Finally, individuals with complementary health insurance plans are less likely to share anonymized test results with their insurer. Using framings for the payment of genetic tests, we grasp the effect of the insurer as a payer on both willingness to undertake the test and readiness to anonymously share the results. Our results indicate a positive effect of the insurer as a payer on the willingness to undertake the test (+24.8%) as well as the results shared with the health insurer (+ 9.4%).

Note: This paper is a joint work with J. Wagner. Financial support was provided by the Swiss National Science Foundation, grant no.CRSII5180350.

6.1 Introduction

Genetic tests (GT) have several purposes: in the case of a healthy individual, sequencing parts of the genome helps to evaluate the risk of developing a certain disease as well as to pass it to the next generation (Perkins et al., 2018). Newborn screening can reveal disorders which need early medication. Diagnose testing, which happens in the case of a sick individual, allows the medical team to understand the genetic root of the condition and to select the treatment which will present the least side effects (Jin et al., 2019; Lima et al., 2019). Finally, direct-to-consumer genetic tests allow individuals to obtain a genetic screening without health care intermediaries. The tests can provide genetic-based food intolerances, exercise plans and in certain cases, a risk profile for specific diseases such as breast cancer (see, e.g., Su, 2013).

In genetic tests' data lies the very strong power of information. This information gives the individual knowledge about the own risk level of a disease and hence the leverage to act on it. For example, by accordingly changing the lifestyle (Horne et al., 2018), one can reduce the probability of this disease to happen. Further, the results of the GT, enable enlightened decisions and to schedule a personalized check-up plan for the individual, to monitor those specific risks (McGeoch et al., 2019). Finally, researchers as an actor of the health ecosystem, can run analyses with the anonymized data to understand which types of prevention work best for which predisposition to a disease. From a social sciences perspective, among the first steps to unlock the benefits of GT, is to understand what drives individuals to take them. To grasp the general public attitude towards GT and its willingness to undergo them provides policymakers and insurers with insights useful to promote their uptake. However so far, several authors in the literature solely focus on a particular condition to assess readiness to undertake genetic testing. For instance, cancer susceptibility risk assessment is a recurrent subject under study for GT willingness (see, e.g., Fogel et al., 2017). Often, the surveyed population and the criteria for an admittance in a particular study usually include family history and being at risk (Dalpe et al., 2017).

In this paper, to fill the gap, we provide a general study of the willingness to undergo GT and share the related data, using novel data from an ad hoc survey carried out in Switzerland. We determine the factors influencing the uptake and sharing of data from GT. Through regression analyses followed by a random forest robustness check, we use five sets of variables, socio-economic, lifestyle, health insurance, sentiment and political beliefs, and two framings. The two framings assess the willingness to undertake the test and the readiness to share anonymized results of the test with the health insurer when the costs of the tests are either borne by the insurer or by the individual. Moreover, our survey design adds the effect of the payer dimension to our analysis through the framings. Including the health insurer as an actor has seldom been done and brings new results to this pane of the GT literature.

Our paper hence focuses on two research questions:

1. What factors explain the genetic test willingness ? To assess this question, we consider regressions with five categories of variables, namely, socioeconomic, lifestyle, insurance, political and sentiment factors. We firstly regress them by categories separately and in a total regression subsequently. To test the robustness of our results, we use a random forest approach on the total regression model to get an importance ranking of the effects.

2. What role does the payer play in the GT willingness and sharing of the anonymized related data ? To answer our second research question, we have designed a survey which not solely allows for the inclusion of various factors but also captures the effect of the insurer as a payer in an additional manner by framing. The framing consists of dividing the sample into two equally-sized subsamples, with each sample being presented with a different framing. After presenting the price range for GT, we display two different sentences introducing two different payers. For the first subsample, the framing suggestes that the GTs should be paid by the health insurer. For the second group, it says that the individual him/herself should pay for the test.

We find that socio-economic, lifestyle or political belief variables have very little or no influence on the uptake of GTs and the sharing of the results with an insurer, which is in line with the literature (Sweeny et al., 2014). On the contrary, our results indicate that insurance and sentiment factors play a strong role. More precisely, if GTs are perceived as a mean to perform health prevention, this pushes individuals to take them by an increase in propensity of 10.9 pp. Further, using the health insurer's smartphone app leads to an increase of 16.5% in the willingness to undergo a GT and of 27.6% to anonymously share the related data with the insurer. Regarding insurance plans and deductible levels, there is no strong correlation neither with the willingness to uptake the test, nor to share the data. Finally, individuals with complementary health insurance plans are less likely to share anonymized test results with their insurer. Using framings for the payment of GTs, we seize the effect of the insurer as a payer on both willingness to undertake the test and readiness to anonymously share the results. Our results indicate a positive effect of the insurer as a payer on the willingness to undertake the test (+24.8%) as well as the results sharing with the health insurer (+9.4%).

The remain of the paper is organised as follows: Section 6.2 offers a literature review along the research questions and the methodology, as well as a description of the variables with descriptive statistics. Section 6.3 and 6.4 present both regression and random forest results. Finally, in Section 6.5 we conclude and provide a discussion for further research.

6.2 Literature review, survey setup and descriptive statistics

6.2.1 Literature review

The state of the existent literature is best described by Sweeny et al. (2014) as being "[...] rife with conflicting findings, inconsistent methodology, and uneven attention across test types and across predictors of genetic testing decisions". One can find in the academic research several clusters of studies. They differ either by the nature of the GTs submitted for questioning or by the population under study. Firstly, the research we encountered mostly focuses on the willingness to do (WTD) or willingness to pay (WTP) a particular GT related to a certain disease, such as breast cancer (e.g., Armstrong et al., 2000), Alzheimer's disease (e.g., Kopits et al., 2011) or colon cancer (e.g., Lerman et al., 1996). Few papers queries on the WTD or WTP for genetic testing in general. Secondly, in many studies, the subject population is targeted and not randomly selected. The selection of the sample is usually based on criteria such as being at-risk for a certain condition. For instance, in the case of Dalpe et al. (2017), women between 35 and 55 years were inquired about their interest to undergo genetic testing in search of a mutation which may lead to breast cancer. Following this restricted selection, the sample size usually ends up in less than 1 000 individuals. Finally, a lot of research is conducted under a social sciences perspective rather than economical view point, hence we found very seldom health insurance as being an examined factor for genetic testing willingness. When the health insurer was mentioned, it was mostly presented in the perceived barriers section as a possible discriminator following a GT. As an instance, the fear of denial for coverage is discussed in multiple papers (e.g., Hall et al., 2005; Allain et al., 2012; Haga et al., 2013; Clayton et al., 2018).

Regarding drivers of GT decision, socioeconomic factors are the first to be assessed. They include age, gender, education, employment status, marital status and income. Throughout our literature review, we did not find consistent results for any of these factors. For instance, in Armstrong et al. (2000) and Miron-Shatz et al. (2015), older women are more likely to undergo GT for breast cancer than younger ones. In Tubeuf et al. (2015) or Wessel et al. (2016), however, age does not play a role in interest for genetic testing for retinal disease or diabetes type 2, respectively. These conflicting findings are backed up by Sweeny et al. (2014), in their literature review. The authors find likewise that age has an unclear outcome on genetic testing decision making. They have also assessed the effects of the aforementioned socioeconomic factors and the results are the same to what is observed more recently by Wessel et al. (2016). Regarding socio-economic factors, the results found in the literature do not reach a consensus either. Predictors such as gender, education, income, or marital status present different effects on GT decisions. Throughout the papers, results are ranging from a positive, to negative effect with most studies not giving conclusive results.

Another interesting factor is the family health history, i.e. the existence or not in the close family of an individual who is suffering or suffered from a given health condition. Expectedly, in a majority of papers, the existence of a family member bearing a particular condition leads

to an increase in the likelihood/willingness of the individual to undergo genetic testing. Blouin-Bougie et al. (2018), Abdul Rahim et al. (2020) and Sun et al. (2020), to cite a few, document such results. Interestingly, a research on a sample of 1 960 British individuals by Sanderson et al. (2004) presented opposing findings for willingness for genetic screening for heart disease or cancer predisposition. In their results, individuals with a family history of heart disease are more likely to do genetic testing for heart disease whereas individuals with cancer running in their family are less likely to undergo genetic testing for cancer. Again, in their systematic review of the literature, Sweeny et al. (2014) confirmed that family health history displays either a positive relationship with GT or no statistical relevance.

Despite the heterogeneity in socioeconomic factors, the literature nevertheless presents several consistent drivers displaying a clear effect on the WTD or WTP. These drivers are psychological and they reflect the individual's view of the gains or losses a GT may result in. They are usually part of the health belief model (Rosenstock, 1974), more precisely the perceived benefits and barriers of the tests, health motivations and perceived susceptibility or severity. The most extensive literature is found on the effect of perceived benefits of genetic testing. These benefits can take several forms like the knowledge about the risks of getting a particular condition (e.g., Gollust et al., 2012; Wessel et al., 2016; Fogel et al., 2017; Kauffman et al., 2017; Abdul Rahim et al., 2020), have adequate prevention (e.g. Lerman et al., 1996; Alanazy et al., 2019) or inform relatives of a possible risk (e.g. Smith and Croyle, 1995; Armstrong et al., 2000; Hall et al., 2005; Fogel et al., 2017; Sun et al., 2020). These benefits are incentives for individuals to undergo testing and hence have a positive impact on the willingness. This is consistent and statistically significant throughout the literature (Sweeny et al., 2014). The perceived barriers also play a role in the GT uptake decision. The most common fears are the financial consequences of the testing (e.g., Bosompra et al., 2000; Alanazy et al., 2019; Sun et al., 2020) and the possible discrimination by employers and insurers (e.g., Lerman et al., 1996; Armstrong et al., 2000; Cameron et al., 2009; Dalpe et al., 2017).

In regard to the shortcomings presented earlier, the aim of our research is twofold. Our study builds on an original survey to address several gaps in the literature. By randomly selecting a representative sample of participants, we ensure the understanding of genetic testing willingness (GTW) and sharing willingness (SW) of the related data in a broad, lay population. Additionally, the size of the sample gives us the opportunity to add a dimension using the payer of the GT as a framing.

6.2.2 Survey setup

To conduct our study, we created an original survey for which the collection of data was supported by a professional polling agency. The sample comprises 1 000 respondents evenly distributed by gender, by four age categories between 25 and 65 years and language regions with two thirds from the German-speaking part and one third from the French-speaking part.

After briefly explaining the purpose of GTs in the context of personalized health, we inquire individuals whether they are using or would be willing to use such type of technology. Subsequently, we focus on GTs and question individuals about factors which could incentivize or refrain them from performing such a test. We take advantage of this focused section to also analyze the effect of the price and the payer on individuals' enthusiasm to do the GT through framing with different scenarios. Finally, we ask socioeconomic, sentiment and political questions.

Response variables: would you carry out such a genetic test?

The core of our questionnaire starts with an introductory paragraph providing the basic knowledge for the surveyed individuals and to set boundaries for a common understanding of genetic testing in the present research.

In Figure 6.1 hereafter, one can observe that we first question the willingness for GT without price information (questions A and B). Subsequently, the whole sample is then divided into two subsamples of randomly selected 500 individuals. The framing targets the payer of the GT. In Framing 1, the payer is the health insurer (question C1), whereas in Framing 2, it is the individual (question C2). Once the question about GTW following the framing is asked, both subsamples are inquired about the willingness to share anonymized data with the health insurer(question D). We report relevant excerpts of the questionnaire in the Appendix. The questions A, B, C1, C2 and D correspond to the questions C3, C4, C5c, C5d and C6, respectively.

Explanatory variables

The first questions of our survey were "selective" questions. These questions inquired about age, gender and postal code to select the respondents, and balance the panel according to the criteria. The majority of the other questions leading to our explanatory variables were asked after the core questions. The first set of questions relates to socioeconomic factors and is composed of ten variables. The second and third sets are insurance and lifestyle factors, containing four and six variables respectively. The fourth set is made of political factors with three variables. The last set is the largest, assembling 24 variables regarding sentiment factors. Several variables present binary categories. Indeed, for some of them, the original categories were merged to create a binary outcome as to decrease the length of the model and avoid a potential overfit. Table 6.1 provides the list of all the used variables, a brief description of the variable itself, accompanied by the available categories, along the five sets of variables.

Socioeconomic factors This set starts with a question asking the survey respondent to indicate the gender with two choices of response, male or female. For the age, we collected integers which were gathered in four classes according to our selection criteria, each class containing 25% of the sample. The classes are 25–34, 35–44, 45–54 and 55–65 years. The last selective variable

Variable	Description	Categories
Socioeconomic factors		
Gender	Gender of the respondent	Male, female
Age	Age class in years	25–34, 35–44, 45–54, 55–65
Region of residency	Canton defined by the spoken language	French-speaking, German-speaking
Nationality	Nationality of the respondent	Other, Swiss
Education	Higher education (above high school level)	No, yes
Professional situation	Current employment situation	Full-time employed, part-time employed, other
Subjective wealth	Subjective household wealth	Below average, above average
Marital status	Marital status	Married / registered partnership, other
Health	Self-rated health	Bad, average, good
Cancer history	History of cancer, cardiac or hereditary disease in close family	No, yes
Lifestyle factors		
Alcohol consumption	Alcohol consumption	Everyday, sometimes, never
Cigarette consumption	Smoking habit	Everyday, sometimes, never
Greens consumption	Fruits and vegetables consumption	Everyday, sometimes, never
Sport	Exercising habit	At least once a week, less
Future planning	Interest of planing for the future	0 to 1 by increments of 0.1
Risk-loving	Readiness to take risks	0 to 1 by increments of 0.1
Insurance factors		
Insurance plan	Mandatory health insurance plan	Basic, Health Maintenance Organisation, family doctor, CallMed
Deductible	Mandatory health insurance level of deductible	CHF 300, {500–2 000}, 2 500
Complementary insurance	Complementary health insurance	No, yes
Insurer's app	Insurer's app for step or exercise count	No, yes
Political factors		
Interest in politics	Interest in politics	No, yes
Political orientation	Political orientation assigned on the left	0 to 1 by increments of 0.1
Feeling close to a political party	Feeling close to a political party	No, yes
Sentiment factors		
Incentive: curiosity	Curiosity is an incentive to undergo genetic testing	No, yes
Incentive: better health prevention	Take better care of health is an incentive to undergo genetic testing	No, yes
Incentive: help relatives care health	Help relatives to take better care of their health is an incentive to undergo genetic testing	No, yes
Incentive: incentivize relatives	Incentivize relatives is an incentive to undergo genetic testing	No, yes
Incentive: disease risk information	Disease risk information is an incentive to undergo genetic testing	No, yes
Barrier: fear of discrimination	Fear of discrimination is a barrier to undergo genetic testing	No, yes
Barrier: test too costly	Fear of cost of test is a barrier to undergo genetic testing	No, yes
Barrier: family disapproves	Fear of family disapproving is a barrier to undergo genetic testing	No, yes
Barrier: lifestyle changes	Induced lifestyle changes is a barrier to undergo genetic testing	No, yes
Barrier: not want info	Not wanting to know the risks is a barrier to undergo genetic testing	No, yes
Barrier: family finances	Impact on family finances is a barrier to undergo genetic testing	No, yes
Impact: more difficult family insured	It will be more difficult for my family to get insured	No, yes
Impact: longer and better life	GT will promote a healthier and longer life	No, yes
Impact: GT will be common	Genetic testing will be common	No, yes
Impact: GT to be hired	GT will be necessary to get hired	No, yes
Impact: sequencing for premium calculus	Sequencing asked prior premium establishment	No, yes
Impact: genetic passport	Everyone will have a genetic passport	No, yes
Impact: discrimination good/bad	There will be a segregation between "good" and "bad" genomes	No, yes
Impact: discrimination of disabled	Disabled individuals will be discriminated	No, yes
Impact: government powerless	Government will not be able to protect individuals	No, yes
Impact: genome sequencing for infants	all infants will have their genome sequenced	No, yes
Impact: all fœtuses genetic testing	All fœtuses will undergo genetic testing	No, yes
Usage of health-related apps	Usage of health-related apps	No, yes
Usage of health-related apps for prevention	Usage of health-related apps for prevention	No, yes

Table 6.1: Summary of the variables along the five sets

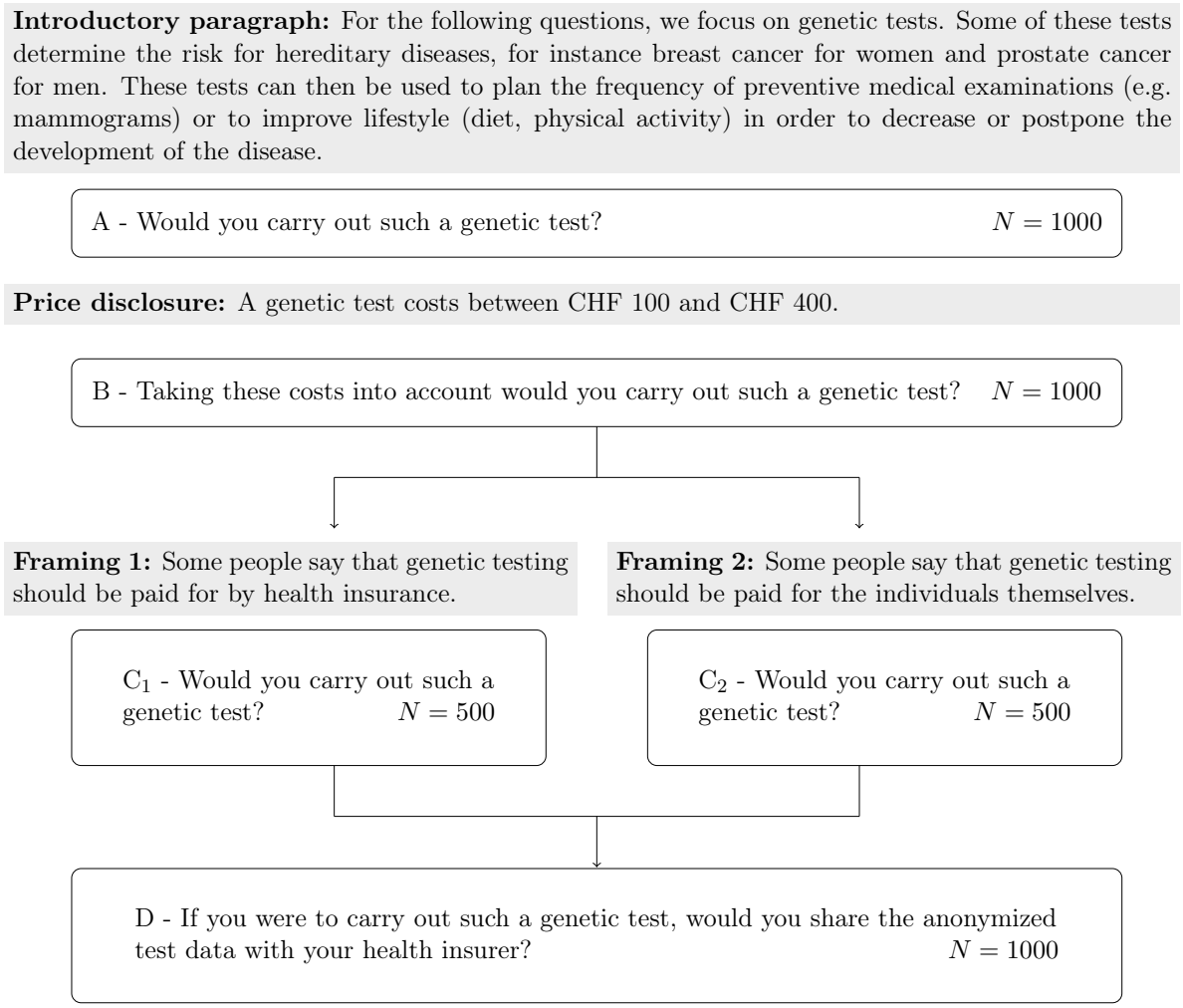


Figure 6.1: Survey setup, core questions and framings

is the region of residency, which can be German- or French-speaking depending on the postal code indicated by the individual. We also collect information about the respondent's nationality (Swiss/other) and education (below or above high school level). Another question concerned the professional situation, to which the responses were merged into "full-time employed", "part-time employed" or "other" categories. We subsequently asked about the subjective wealth of the individual which could be answered by below or above average and the marital status, which can be either "married/in a registered partnership" or "other". Finally the last two questions of this set deal with health. In one question the respondents had to rate their health from "very bad", "bad", "fairly good", "good" and "very good", which response we classified into "bad" for the two worst levels, "average" for the middle level and "good" for the two best levels chosen. The last question is whether the participant has a history of cancer, cardiac or hereditary disease in the immediate family.

Insurance factors This set relates to the health insurance subscribed by the individual. In Switzerland, the mandatory health insurance policy has two features: the plan and the annual deductible. Hence, the first question inquires about the insurance plan, which can be of several

nature: basic, Health Maintenance Organisation, family doctor or CallMed. The second question regards the deductible which can be CHF 300, CHF 500, CHF 1 000, CHF 1 500, CHF 2 000 or CHF 2 500. Usually, it is the two extremes that are favored, hence we merged the levels in the middle (CHF 500 to 2 000) to obtain a three-level scale. Alongside the mandatory health insurance, the individual can take out an optional complementary insurance, we therefore ask if he/she holds such a policy. Lastly, we have a variable (insurer's app) indicating whether the person has an app from his/her health insurance for recording activity or counting steps.

Lifestyle factors Three questions start by inquiring the individual about his/her habits. These questions concern alcohol, cigarettes and greens (vegetables and fruits) consumption, to which the possible responses were: daily, several times a week, once a week, once every two weeks, once a month, less regularly or never. We subsequently merged the responses to obtain a three-level categorical variable with "everyday", "sometimes" and "never" as outcomes. Physical exercise (sport) was also taken into account by a question asking the frequency at which the individual exercises. The possible answers being several times a week, once a week, less regularly and never were pooled together to create a binary variable : at least once a week or less. To conclude this set, we dig deeper into the person's behaviour by asking for his/her interest for planing for the future, together with readiness to take risks. The answers were based on an 11-points Likert scale ranging from "not interested at all" to "very interested" (future planning / risk-loving).

Political beliefs factors Our fourth and shortest set includes three questions about political beliefs. In the first question, individuals had to express their interest in politics from the possible "not at all interested", "slightly interested", "fairly interested" or "very interested" answers. The second question asked the individual to rate his/her political orientation on an 11-point Likert scale going from "left" to "right". For the last question, we presented several political parties (with the "another / several parties", "I do not want to disclose", "I do not relate to any" options) and asked the person to select which party they feel the closest to. We then extracted a binary outcome indicating if the participant felt close to a political party or not.

Sentiment factors This last set is the most furnished with 22 variables stemming from three questions and two additional health-related apps questions. In the three first questions, several statements are given to which the respondent had to chose a level of agreement on a five-point Likert scale ranging from "strongly disagree" to "completely agree". Subsequently, we code the answers as "is an incentive" for individuals ticking the "completely agree" and the following level and "not an incentive" for the other responses.
The first question suggests incentives to undergo genetic testing: I am curious about my genetic makeup; my results could help me take better care of my health; my results could help my relatives to take better care of their health; it could incentivize my relatives to undergo genetic testing for themselves and my results could provide useful information about my hereditary

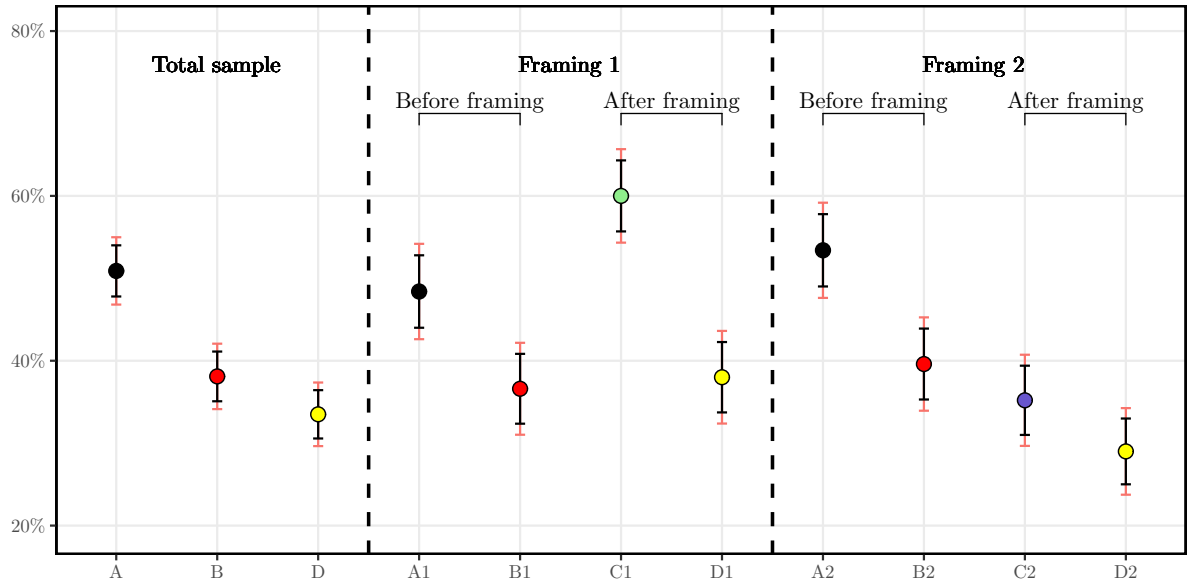
diseases or my risk cancer.
Similarly, the second question cites potential barriers to genetic testing. These hurdles being: I fear a possible discrimination; I fear the test would be too expensive; some members of my family could disapprove me taking a test; knowing my cancer risk may force me to lead a different lifestyle; I don't want to know what potential illness I might have in the future; I think my results could have a strong impact on my family's finances.
Ultimately, to capture the outlook of the individual on GT and his/her beliefs regarding GT developments, we have a series of 11 questions. The following sentences were displayed to which the respondent had to chose a level of agreement. It will be more difficult for my family members to get an insurance policy. Knowledge related to genetics will lead to fewer illnesses and longer life expectancy. It will be very common to perform genetic tests. Future employees will have to undergo genetic testing before being hired. Insurance companies will request a sequencing of our genome to establish premium levels. In the future we will all have a genetic passport. There will be a segregation in our society between "good" and "bad" genomes. People with disabilities will be less accepted in society. The government will not be able to protect citizens from the negative aspects of genetic testing. The genome of all infants will be sequenced to establish their genetic profile and prevent development of certain diseases. Finally, all pregnant women will undergo genetic testing to determine if the fœtus carries a disease.

6.2.3 Descriptive statistics

Response variables: would you carry out such a genetic test?

In this section we perform a statistical analysis on the responses derived from the core questions presented in Section 6.2.2. In Figure 6.2, we display the mean values and confidence intervals for the answers to each question. The figure is divided in three sections. The left section represents the means of the whole sample of 1 000 individuals, the middle section represents the means of the subsample presented with the first framing, insurer as a payer, and the right section, the subsample from the second framing, individual self-payer. On the left of each section of the figure, the black dot illustrates the mean level of agreement in question A in Figure 7.1 for the whole sample, for the insurer payer framing in the middle and on the right for the self payer framing. The same logic applies to the red and yellow dots, which represent the means for questions B and D. In the second section, the green dot concerns the answers for those who had the insurer framing and the blue dot represents the answers for the self-payer framing. Additionally, the red line represents a 99% confidence interval and the black line a 95%. The numbers corresponding to the 95% confidence interval can be found in Table 6.2.

As one can firstly see, for the result of the baseline GTW, half of individuals (50.9%) agreed that they would be willing to undergo a GT. The distribution of this answer is not statistically different in the framed groups. Comparing with similar studies, in a randomly selected sample of 383 individuals by Smith and Croyle (1995), 47.3% of the interviewees stated that they are very



Note: A_1 and A_2 correspond to the level of agreement for question A in each subsample of $N = 500$ respectively. B_1 and B_2 correspond to the level of agreement for question B in each subsample of $N = 500$. C_1 and C_2 correspond to the level of agreement for question C in each subsample of $N = 500$.

Figure 6.2: Confidence intervals at 95% and 99% for GTW

		Total		Framing 1		Framing 2	
Question		Agree	$CI_{95\%}$	Agree	$CI_{95\%}$	Agree	$CI_{95\%}$
A	GTW	50.9%	[47.8; 54.0]	48.4%	[44.0; 52.8]	53.4%	[49.0; 57.8]
B	GTW price bracket	38.1%	[35.1; 41.1]	36.6%	[32.4; 40.8]	39.6%	[35.3; 43.9]
C1	GTW insurer payer			60.0%	[55.7; 64.3]		
C2	GTW self payer					35.2%	[31.0; 39.4]
D	SW	33.5%	[30.6; 36.4]	38.0%	[33.7; 42.3]	29.0%	[25.0; 33.0]
N		1 000		500		500	

The abbreviations "GT" and "SW" stand for genetic test willingness and sharing willingness, respectively.

Table 6.2: Average level of agreement per variable with 95% confidence intervals

interested in taking a GT for colon cancer and 16.1% that they are not interested. More recently, in a study conducted in Saudi Arabia, authors assessed willingness to undergo presymptomatic genetic testing for Alzheimer's disease and obtained a level of agreement of 59.9% for either one of the two presented GTs and 45.1% for both tests (Alanazy et al., 2019). Our results hence corroborate findings for similar surveys in the literature.

Once price information is displayed, we observe the number of agreeing respondents drop from 509 individuals to 381. We note for this question that, aside from the price range of CHF 100 to CHF 400, no payer was specified. This drop can be explained by the fact that the price may be higher than expected or renders the test more tangible as knowing the price brings the individual closer to the concept of buying the product. Another explanation could be the price itself, which can be a burden for some individuals. It will be interesting to test this hypothesis in the regressions with the income variable. Additionally, the two samples used int the framings

do not have statistically different means with 99% confidence.

Subsequently, when the framings are applied, a clear cut appears. For the group framed with the insurer as a payer, the share of surveyed individuals agreeing to undergo the testing increases to attain 60.0% whereas those framed to be the sole payer of the test decreases as low as 35.2%. These means are statistically significantly different at 95% as their confidence intervals do not overlap. One can hypothesize that the insurer as a payer triggers more individuals to undergo the test because of the cost relief. We later test this hypothesis with regressions to understand the difference between potential drivers of the GTW.

Finally, interesting results can already be seen for the SW of anonymized data from GTs with the health insurer. When merged together, the whole sample exhibits a willingness to share of 33.5%. However, in the subsamples, we observe a clear cleavage. Indeed, the two groups display statistically significantly different means at a confidence level of 95%, hinting that the role of the payer is essential in this regard. Regression analysis allows us to study this relationship and suggest possible correlation between the payer and the readiness of an individual to share health-related data with the insurer.

Explanatory variables

In a preliminary analysis, we have a look at the descriptive statistics for the socioeconomic, insurance, lifestyle and political beliefs in Table 6.3, and in Table 6.4 for the the sentiment factors. For each variable, the sample column displays the frequency of the variable in the whole sample. In the four following columns, we display the level of agreement to the questions introduced in Section 6.2.2, i.e.: A – genetic testing, B – genetic testing after price display, C1 – genetic testing with insurer as a payer, C2 – genetic testing with the individual as a payer, and D – data sharing with the health insurer, by variable.

Considering the descriptive statistics, we get a hint on possible correlations between the explanatory variables and the core questions. In the first set of variables, the socioeconomic factors, two variables stand out – age and nationality. Noticeable changes in the share of individuals who are willing to either undergo the test or share the data take place for the older group in the sample. For instance, the GTW in the group 55–65 years drops by as much as 18 percentage points (pp) when compared to the 35–44 in question A. This gap increases to 25 pp for the GTW when the insurer is the payer (C1). This difference is also true for SW with a disparity of 11 pp between the two groups. The older individuals in our sample seem to be reluctant to taking a GT as well as sharing the related anonymized data with their health insurer. We hence expect this effect to emerge in the regressions. The same conclusion can be drawn for the Swiss nationals in our sample. As a matter of fact, disregarding the price display or the payer of the test, they present a lower level of GTW and SW, suggesting that Swiss are less open to these ideas. Moving on to insurance factors, some sparse but clear effects can be seen from having a complementary health insurance. The strongest positive effect for those who declared holding

Variable	Sample (%)	Level of agreement A	B	C1	C2	D	Variable	Sample (%)	Level of agreement A	B	C1	C2	D
Socioeconomic factors													
Gender							**Health**						
Male	50.0	0.50	0.38	0.60	0.37	0.37	Bad	7.5	0.49	0.37	0.50	0.30	0.31
Female	50.0	0.52	0.38	0.60	0.34	0.30	Average	33.7	0.51	0.36	0.66	0.33	0.38
Age							Good	58.8	0.51	0.40	0.58	0.37	0.31
25–34	25.0	0.54	0.40	0.68	0.42	0.35	**Professional situation**						
35–44	25.0	0.58	0.42	0.71	0.37	0.37	Full time employed	51.6	0.52	0.41	0.63	0.39	0.35
45–54	25.0	0.51	0.38	0.54	0.33	0.36	Part-time employed	27.8	0.45	0.33	0.52	0.31	0.31
55–65	25.0	0.40	0.32	0.46	0.30	0.26	Other	20.6	0.58	0.37	0.64	0.32	0.33
Nationality							**Subjective wealth**						
Other	25.5	0.64	0.50	0.76	0.45	0.39	Below average	58.9	0.49	0.36	0.60	0.29	0.35
Swiss	74.5	0.47	0.34	0.55	0.31	0.32	Above average	41.1	0.53	0.40	0.60	0.45	0.31
Higher education							**Marital status**						
No	61.3	0.48	0.35	0.59	0.33	0.39	Married / Partnership	52.2	0.53	0.40	0.58	0.38	0.31
Yes	38.7	0.56	0.42	0.62	0.38	0.31	Other	47.8	0.49	0.36	0.62	0.32	0.36
Cancer history							**Region**						
No	54.0	0.48	0.37	0.61	0.36	0.34	French-speaking	33.0	0.55	0.38	0.67	0.35	0.29
Yes	46.0	0.55	0.39	0.60	0.34	0.33	German-speaking	67.0	0.49	0.38	0.57	0.36	0.36
Insurance factors													
Insurance plan							**Deductible**						
Basic	26.2	0.53	0.43	0.60	0.40	0.31	CHF 300	40.5	0.52	0.37	0.59	0.30	0.32
HMO	9.9	0.47	0.34	0.60	0.27	0.40	CHF {500; 2 000}	28.0	0.50	0.38	0.69	0.41	0.38
Family Doctor	51.9	0.50	0.36	0.60	0.35	0.35	CHF 2 500	31.5	0.50	0.41	0.61	0.40	0.32
CallMed	12.0	0.51	0.38	0.62	0.32	0.25							
Complementary insurance							**Insurer's app**						
No	33.2	0.50	0.31	0.62	0.28	0.37	No	80.3	0.48	0.34	0.62	0.33	0.29
Yes	66.8	0.51	0.41	0.59	0.39	0.32	Yes	19.7	0.63	0.53	0.59	0.45	0.54
Lifestyle factors													
Alcohol							**Smoking**						
Everyday	3.6	0.47	0.42	0.65	0.13	0.36	Everyday	25.2	0.53	0.40	0.58	0.35	0.32
Sometimes	78.2	0.51	0.39	0.60	0.37	0.34	Sometimes	18.1	0.57	0.40	0.36	0.66	0.41
Never	18.2	0.51	0.35	0.59	0.33	0.31	Never	56.7	0.48	0.37	0.60	0.35	0.32
Five servings of greens							**Sport**						
Everyday	23.7	0.53	0.44	0.62	0.40	0.35	At least once a week	66.5	0.53	0.40	0.60	0.32	0.36
Sometimes	75.5	0.50	0.37	0.60	0.34	0.33	Less	33.5	0.46	0.35	0.60	0.37	0.30
Never	0.8	0.25	0.00	0.00	0.25	0.38							
Planing for the future							**Risk loving**						
1	3.5	0.29	0.20	0.42	0.13	0.17	1	5.3	0.45	0.36	0.54	0.37	0.26
2	1.9	0.32	0.21	0.50	0.15	0.53	2	4.5	0.36	0.22	0.52	0.08	0.22
3	3.7	0.30	0.24	0.39	0.29	0.16	3	8.5	0.41	0.27	0.53	0.21	0.31
4	4.0	0.40	0.15	0.67	0.20	0.45	4	8.7	0.54	0.43	0.61	0.34	0.36
5	6.7	0.39	0.16	0.38	0.21	0.34	5	12.7	0.42	0.31	0.48	0.29	0.28
6	11.0	0.38	0.29	0.45	0.29	0.27	6	17.4	0.54	0.40	0.60	0.46	0.32
7	17.1	0.44	0.35	0.53	0.53	0.30	7	19.0	0.52	0.36	0.61	0.37	0.34
8	22.9	0.58	0.42	0.66	0.66	0.34	8	12.4	0.57	0.49	0.67	0.40	0.40
9	13.1	0.57	0.48	0.68	0.68	0.40	9	4.7	0.64	0.43	0.67	0.35	0.38
10	16.1	0.71	0.57	0.83	0.83	0.43	10	6.8	0.60	0.51	0.76	0.43	0.47
Political factors													
Interest in politics							**Feeling close to a political party**						
No	53.2	0.49	0.36	0.60	0.34	0.33	No	44.7	0.50	0.36	0.60	0.36	0.32
Yes	46.8	0.53	0.41	0.60	0.37	0.34	Yes	55.3	0.52	0.40	0.60	0.35	0.35
Political orientation													
Left	4.0	0.55	0.40	0.62	0.37	0.38							
	3.8	0.53	0.42	0.60	0.43	0.24							
	8.7	0.40	0.29	0.43	0.32	0.25							
	8.1	0.60	0.58	0.61	0.45	0.37							
	9.5	0.49	0.37	0.61	0.40	0.35							
Center	30.6	0.51	0.38	0.63	0.33	0.33							
	9.1	0.52	0.36	0.57	0.37	0.43							
	10.1	0.46	0.30	0.52	0.31	0.31							
	6.3	0.44	0.35	0.51	0.33	0.25							
	3.5	0.69	0.43	0.71	0.44	0.54							
Right	6.3	0.59	0.43	0.64	0.29	0.33							
N	1 000	1 000	1 000	500	500	1 000		1 000	1 000	1 000	500	500	1 000

Table 6.3: Descriptive statistics: willingness for genetic testing and data sharing per variable

a complementary insurance policy intervene when cost comes into play, i.e. when the price is displayed or when the individual is the payer of the GT. On these GTW, the increase is by roughly 10 pp. Additionally, the correlation between having an insurer's app for step or exercise

Variable	Sample (%)	Level of agreement A	B	C1	C2	D	Variable	Sample (%)	Level of agreement A	B	C1	C2	D
Sentiment factors													
Is an incentive to undergo genetic testing							**Is a reason not to undergo genetic testing**						
Curiosity							Impact on family finances						
No	48.2	0.26	0.17	0.16	0.40	0.25	No	72.1	0.50	0.38	0.56	0.36	0.43
Yes	51.8	0.74	0.57	0.80	0.52	0.41	Yes	27.9	0.54	0.39	0.71	0.34	0.41
Take better care of my health							Family disapproves						
No	44.5	0.25	0.18	0.37	0.17	0.23	No	79.7	0.51	0.37	0.60	0.36	0.31
Yes	55.5	0.72	0.54	0.79	0.49	0.42	Yes	20.3	0.50	0.41	0.59	0.34	0.41
Diseases risk information							Fear test too costly						
No	37.0	0.22	0.17	0.33	0.18	0.26	No	44.5	0.49	0.41	0.53	0.39	0.33
Yes	63.0	0.68	0.51	0.76	0.45	0.38	Yes	55.5	0.52	0.36	0.66	0.32	0.34
Help my relatives take better care of themselves							Do not want the info						
No	53.9	0.33	0.23	0.41	0.23	0.25	No	62.0	0.60	0.44	0.71	0.39	0.34
Yes	46.1	0.72	0.55	0.81	0.50	0.43	Yes	38.0	0.36	0.28	0.45	0.27	0.32
Could incentivize my relatives to undergo a test							Induced lifestyle changes						
No	61.7	0.36	0.26	0.45	0.24	0.26	No	56.0	0.46	0.33	0.53	0.34	0.29
Yes	38.3	0.75	0.58	0.85	0.53	0.46	Yes	44.0	0.57	0.45	0.68	0.37	0.39
Impact of genetic tests on society							Fear of discrimination						
More difficult family members to be insured							No	75.9	0.54	0.38	0.61	0.36	0.34
No	63.4	0.52	0.38	0.62	0.34	0.35	Yes	24.1	0.42	0.37	0.55	0.32	0.33
Yes	36.6	0.49	0.37	0.57	0.37	0.32	**Impact of genetic tests on society**						
Genetic tests will be common							Fewer illnesses and longer life expectancy						
No	62.4	0.41	0.27	0.54	0.23	0.27	No	56.0	0.39	0.26	0.47	0.24	0.26
Yes	37.6	0.68	0.56	0.71	0.56	0.44	Yes	44.0	0.66	0.54	0.76	0.50	0.43
Sequencing prior to premium establishment							Genetic testing to be hired						
No	57.4	0.52	0.40	0.59	0.35	0.35	No	81.7	0.50	0.36	0.59	0.33	0.30
Yes	42.6	0.50	0.36	0.61	0.36	0.32	Yes	18.3	0.55	0.46	0.65	0.45	0.49
Segregation between good and bad genomes							Genetic passport for everyone						
No	52.3	0.51	0.36	0.60	0.33	0.35	No	63.5	0.43	0.28	0.53	0.25	0.28
Yes	47.7	0.51	0.40	0.60	0.38	0.32	Yes	36.5	0.65	0.56	0.70	0.56	0.43
Government will not be able to protect							Discrimination towards disabled individuals						
No	49.9	0.59	0.42	0.66	0.38	0.36	No	60.4	0.57	0.39	0.63	0.37	0.36
Yes	50.1	0.43	0.34	0.55	0.31	0.31	Yes	39.6	0.44	0.36	0.55	0.33	0.30
All fœtuses will undergo genetic testing							All infants will have their genome sequenced						
No	54.9	0.45	0.32	0.49	0.30	0.30	No	60.5	0.43	0.31	0.54	0.28	0.28
Yes	45.1	0.58	0.46	0.73	0.43	0.38	Yes	39.5	0.63	0.49	0.70	0.48	0.42
Usage of health-related apps							**Usage of health-related apps for health prevention**						
No	29.8	0.28	0.21	0.38	0.23	0.22	No	52.3	0.53	0.37	0.64	0.31	0.38
Yes	70.2	0.61	0.45	0.70	0.40	0.38	Yes	47.7	0.70	0.55	0.76	0.50	0.39
N	1 000	1 000	1 000	500	500	1 000		1 000	1 000	500	500	1 000	

Table 6.4: Descriptive statistics: willingness for genetic testing and data sharing per variable

count and GTW as well as SW is quite strong and positive. Going to the next set, the lifestyle factors, only one variable has a clear and consistent pattern along its categories. Indeed, as the level of interest of planing for the future increases, so does the share of individuals who present a positive GTW and SW. As an example, for question A, the proportion of individuals who would be willing to get a GT rises from 29% among individuals who indicated having the lowest level of interest in future planing to 71% for those who have the highest.

For the last set on Table 6.3, the political factors, it is difficult to establish any hypothesis on the impact of these variables. The GTW proportions do not seem to follow a clear pattern and to display any correlation.

Table 6.4 contains the sentiment factors. The related variables come from three categories of questions: potential incentives for GTs, potential barriers to genetic testing and impact of genetic testing on society. We first focus on the potential incentives to undergo genetic testing. According to our statistics, for each variable, there is a strong discrepancy between individuals who agreed with the statement and those who did not. As an example, individuals who agreed being curious about their genetic makeup is a good incentive for them to get GT are almost

three times more likely to undergo genetic testing as well as share the related anonymized data with their health insurer than those who were not curious. This observation holds for all the variables in the set for a minimum difference of twofold. Regarding the barriers, the divergences in the answers is less striking. Only not wanting to know the risks and the fear of possibly induced life changes are potential factors diminishing GTW. Lastly, for variables indicating the general outlook of individuals on the GT in society, several factors show relevance. One can spot four variables: testing will be common, all fœtuses as well as infants will undergo genetic testing, everybody will have a genetic passport and knowledge based on genetics will increase life expectancy and promote better health. The individuals who agreed with these statements are more likely to undergo genetic testing, consistently throughout all the GTW and SW. Interestingly, those who agreed that genetic tests will be mandatory to be hired are 63% more likely to share anonymized data with their health insurer.

6.3 Regression analysis and results

6.3.1 Methodology

We perform all regressions using the R software. Equation (6.1) describes the regression of each of the interest variables, A, B, C1, C2 and D that we denote W_i. Each W_i is regressed on the five groups of factors, i.e., socioeconomic, lifestyle, insurance, political and sentiment factors variables that form the set of variables X. For W_i, we merged the possible responses into a binary variable taking the value 1 if "likely" or "very likely" was selected, and 0 otherwise. Using Akaike's information criterion (AIC), we selected the logit link function for the regression as it displayed a lower AIC. The following Equation 6.1 is used for all sets of explanatory variables defined by the vector X

$$g(W_i) = \beta_{0j} + \sum_k \beta_{Xjk} X_{jk}, \tag{6.1}$$

Where j represents each group of explanatory factors in the set X and k, each variable within this group. The β_0 and β_{Xjk} coefficients correspond to the baseline, respectively the regression coefficients linked to the variables X_{jk}.

Further on, to facilitate interpretation and comparison between effects, for binary variables, we translated the β_{Xjk} coefficients into their probabilities (expressed in %) of obtaining 1 for W_i. The formula for the effect of a coefficient jk for a particular WIL_i is the following:

$$p_{jk} = \left(\frac{e^{\beta_{0j} + \beta_{Xjk} X_{jk}}}{1 + e^{\beta_{0j} + \beta_{Xjk} X_{jk}}} - \frac{e^{\beta_{0j}}}{1 + e^{\beta_{0j}}} \right) \cdot 100 \tag{6.2}$$

After regressing the four W_i variables separately on the five groups of factors, we perform an overall regression combining all factors in a single regression model. Subsequently, we select the

most relevant variables using a forward and backward variable selection with the stepAIC function in R (Venables and Ripley, 2002).[1] This procedure allows to check for coefficients robustness and capture the most relevant explanatory variables. Finally, as an additional information, we use the randomForest package in R (Breiman, 2001) to obtain an importance ranking of the effect of the variables on the GTW and SW.[2]

6.3.2 Results

In this subsection, we present regression results separately for each of the five sets of socioeconomic, insurance, lifestyle, political beliefs and sentiment factors. For each of the four variables, we display the β coefficients, their equivalent p in terms of probabilities, and the significance. For categorical variables, the baseline is defined by the most frequent category in the sample. Following these regression results, we will present a confusion matrix and perform several robustness checks in Section 6.4.

Socioeconomic factors From Table 6.5, we observe that only few factors are significant drivers for either GTW or SW. As expected from the literature review and the statistical analysis, except for nationality and age, the gender, education, professional status, marital status, wealth and region of residency do not explain responses from individuals. Two regression results however confirm findings from the statistical outlook. The age and Swiss nationality do influence the willingness to undergo genetic testing. As noted by the 18 pp decrease in the individuals aged 55–65 years, their willingness for GTs uptake is distinctively lower than for other categories. They display a reduction by 17% in willingness compared to the baseline categories of 35–44 years. This decrease in willingness is however solely significant in the questions with the baseline willingness (A) and when the insurer is the payer (C1), where we observe a decrease (of -18.5%). The same observation holds for the SW. According to our results, respondents between the ages of 55 and 65 years are 11.9% less likely to share their anonymized GTs result with the health insurer, everything else kept constant. The second variable with significant impact on questions A, B, C1 and C2 is nationality. Individuals with Swiss nationality seem less open to the idea of genetic testing, disregarding the price display or the payer, with strong significance. To conclude with this set of variables, cancer history and health present rather intriguing results. One would hypothesise that an individual who has a case of cancer in his/her close family is more enthusiastic regarding genetic testing but this hypothesis is only statistically verified for the baseline GTW, before any price is given. This inconclusive result can also be found in literature where authors either find a positive (Abdul Rahim et al., 2020; Sun et al., 2020) or a mitigated effect (Sanderson et al., 2004). Similarly, another belief could be that the health of the respondent comes into the decision process to undergo a GT. Our results seem to annihilate such a relationship as the variable does not present significant coefficients. Nevertheless, is it interesting to notice that when the level of agreement for genetic testing drops from question

[1] See `https://www.rdocumentation.org/packages/MASS/versions/7.3-54/topics/stepAIC`

[2] See `https://cran.r-project.org/web/packages/randomForest/randomForest.pdf`.

A to question B when the price range is displayed, wealthier individuals do not seem to be less affected as wealth is not show significant.

Model	**A** – Baseline GTW			**B** – Price display			**C1** – Insurer payer			**C2** – Self payer			**D** – Data sharing		
	β_k	p_k	sig.	β_k	p_k	sig.	β_k	p_k	sig.	β_k	p_k	sig.	β_k	p_k	sig.
Gender (baseline: Male)															
Female	0.099	+2.41%		0.130	+3.22%		0.172	+2.219%		0.000	+0.00%		−0.310	−7.271%	*
Age (baseline: 35 – 44 years)															
25 – 34 years	−0.113	−2.81%		−0.041	−1.00%		−0.164	−2.44%		0.278	+6.73%		−0.047	−1.13%	
45 – 54 years	−0.337	−8.39%		−0.208	−5.06%		−0.790	−13.95%	**	−0.129	−2.99%		−0.047	−1.124%	
55 – 64 years	−0.696	−17.19%	***	−0.313	−7.54%		−0.998	−18.52%	***	−0.196	−4.51%		−0.522	−11.87%	**
Swiss nationality (baseline: No)															
Yes	−0.630	−15.61%	***	−0.635	−14.66%	***	−0.925	−16.88%	***	−0.589	−12.63%	**	−0.292	−6.87%	
Higher education (baseline: No)															
Yes	0.249	+6.00%		0.164	+4.07%		−0.007	−0.13%		−0.023	−0.54%		−0.208	−4.94%	
Professional status (baseline: Full-time employed)															
Part-time	−0.245	−6.08%		−0.336	−8.07%		−0.609	−10.24%	*	−0.219	−5.02%		−0.101	−2.42%	
Other	0.322	+7.70%		−0.110	−2.69%		0.141	+1.83%		−0.206	−4.74%		0.017	+0.40%	
Subjective wealth (baseline: Below average)															
Above average	0.155	+3.78%		0.202	+5.03%		0.052	+0.69%		0.602	+14.81%	**	−0.229	−5.42%	
Married (baseline: No)															
Yes	0.182	+4.40%		0.139	+3.46%		−0.089	−1.30%		0.233	+5.63%		0.229	+5.64%	
Cancer history (baseline: No)															
Yes	0.382	+9.05%	**	0.178	+4.43%		0.002	−0.00%		0.061	+1.44%		−0.045	−1.08%	
Health (baseline: Bad)															
Average	0.069	+1.70%		0.031	+0.76%		0.662	+7.28%		−0.021	−0.50%		0.265	+6.54%	
Good	0.120	+2.93%		0.237	+5.89%		0.346	+4.24%		0.046	+1.09%		−0.005	−0.12%	
Region (baseline: French)															
German	−0.194	−4.81%		0.008	+0.19%		−0.351	−5.49%		0.006	+0.14%		0.313	+7.75%	*
Constant	0.257			−0.227			1.612		***	−0.488			−0.342		
N	1 000			1 000			500			500			1 000		

Note: The significance levels are * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 6.5: Regression results for socioeconomic factors

Lifestyle factors Among the lifestyle factors displayed in Table 6.6, only one variable displays a significant and consistent effect throughout all regressions: being keen on planing for the future. This variable is considered on a scale from 0 to 1, on which the individuals had to place their tendency of planning for the future. According to our results, the higher the level, the more likely is the respondent to undergo a GT, disregarding added information about the price or the payer. The same result is valid for propensity to share anonymized data. This correlation is coherent considering that in our survey we deal with genetic testing for preventive purposes, hence for planning future medical examinations and potential diseases. Other health-related covariates do not affect individuals' decision-making, suggesting that this decision does not necessarily stem from health considerations, as already outlined by the absent correlation with the health variable in Table 6.5.

Political belief factors Regarding political factors, the results from Table 6.7 are clear, there is no correlation between political belongings and GTs decisions. A plausible explanation could be that the subject is too new to be politicised. No party in Switzerland yet has formulated a clear opinion on the subject, neither on the related data. Hence, the belonging to a party or a movement of thought does not translate in a clear differentiation between individuals' responses.

Model	**A** – Baseline GTW			**B** – Price display			**C1** – Insurer payer			**C2** – Self payer			**D** – Data sharing		
	β_k	p_k	sig.	β_k	p_k	sig.	β_k	p_k	sig.	β_k	p_k	sig.	β_k	p_k	sig.
Alcohol consumption (baseline: Everyday)															
Sometimes	−0.185	−0.67%		0.056	+0.00%		−0.200	+0.00%		0.150	+0.75%		0.015	+0.11%	
Never	−0.299	−1.02%		0.179	+0.00%		0.020	+0.00%		−1.123	−3.38%		0.153	+1.79%	
Cigarettes consumption (baseline: Everyday)															
Sometimes	0.591	+3.01%	**	0.298	+0.00%		0.482	+0.00%		0.188	+0.96%		0.502	+6.79%	**
Never	0.349	+1.58%	*	0.223	+0.00%		−0.024	+0.00%		0.152	+0.76%		0.069	+0.75%	
Fruits and vegetables consumption (baseline: Everyday)															
Sometimes	1.097	+7.14%		14.932	+5.91%		16.322	+21.79%		0.298	+1.62%		−0.328	−3.36%	
Never	1.063	+6.81%		15.109	+6.97%		16.376	+22.73%		0.482	+2.87%		−0.339	−3.46%	
Sport at least once a week (baseline: No)															
Yes	0.253	+1.09%		0.115	+0.00%		−0.188	+0.00%		0.153	+0.77%		0.240	+2.94%	
Level of planning for the future															
	0.225		***	0.241		***	0.222		***	0.197		***	0.129		***
Level of loving taking risks															
	0.051			0.053			0.068			0.054			0.059		
Constant	−3.167		***	−17.736			−17.640			−2.967		**	−1.915		**
N	1 000			1 000			500			500			1 000		

Note: The significance levels are * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 6.6: Regression results for lifestyle factors

Model	**A** – Baseline GTW			**B** – Price display			**C1** – Insurer payer			**C2** – Self payer			**D** – Data sharing		
	β_k	p_k	sig.	β_k	p_k	sig.	β_k	p_k	sig.	β_k	p_k	sig.	β_k	p_k	sig.
Political interest (baseline: No)															
Yes	0.151	+3.77%		0.188	+4.47%		0.018	+0.46%		0.184	+4.44%		−0.059	−1.22%	
Feeling close to a political party (baseline: No)															
Yes	0.000	+0.02%		0.107	+2.50%		−0.099	−2.45%		−0.075	−1.76%		0.167	+3.58%	
Political orientation (baseline: Left)															
	0.191	+4.78%		−0.183	−4.15%		0.390	+9.26%		−0.338	−7.59%		0.259	+5.63%	
Constant	−0.131			−0.542		**	0.259			−0.486		*	−0.884		***
N	1 000			1 000			500			500			1 000		

Note: The significance levels are * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 6.7: Regression results for political belief factors

Insurance factors In the set of insurance, we find that the chosen features of the mandatory health insurance (insurance plan and deductible) do not allow to consistently distinguish individuals who are more willing to take a GT. Three other variables, however, allow to do so. In our sample, we document that individuals who hold a complementary health insurance policy display a different behavior. More precisely, the factor comes into play when the decision to undergo genetic testing is faced with the cost, that is, in questions B and C2. For both cases, individuals who do own such a policy are more willing to undergo a GT by 9.33% and 14.70%, respectively, as reported in Table 6.8. A potential explanation could be that individuals with a complementary health insurance are less cost-conscious as the health care costs are alleviated. This usually leads to an increase in health care consumption as highlighted by Schmitz (2012), thus encompassing genetic testing. Another interesting effect induced by this variable is the decrease in willingness to share anonymized results from this GT with the health insurer (question D): having a complementary health insurance renders individuals less likely by 7.92% to share the data. This may be correlated with the fact that the calculation of premiums for complementary health insurance in Switzerland, contrary to basic health insurance is based, among other characteristics, on the health condition and family history. The next variable is binary, indicating whether the individual has an app from the insurer for step counting or recording exercise,

participants who ticked "yes", have an increased willingness to undergo genetic testing, except when the insurer is the payer, in which case the coefficient is not significant. This outcome is rather intriguing and an underlying rationale could be that individuals who are interested in their health in the first place are more likely to download the health app. This interest then makes them more likely to be interested in performing a GT, unless when it is the insurer who is the payer, where more respondents are more interested in general, thus annihilating the significance of the difference. When it comes to sharing the anonymized data from the GT with the health insurer, the same rationale can be applied. In fact, these individuals that already share data from the app with the health insurer are 27.9% (p-value < 0.001) more willing to share GT data.

Model	**A** – Baseline GTW			**B** – Price display			**C1** – Insurer payer			**C2** – Self payer			**D** – Data sharing		
	β_k	p_k	sig.	β_k	p_k	sig.	β_k	p_k	sig.	β_k	p_k	sig.	β_k	p_k	sig.
Insurance plan (baseline: Family doctor)															
Standard	0.164	+0.54%		0.457	+0.61%	**	0.016	+0.50%		0.412	+0.60%		−0.229	−5.11%	
HMO	−0.171	−4.22%		−0.113	−2.18%		−0.060	−1.45%		−0.413	+6.79%		0.040	+0.90%	
CallMed	−0.044	−1.10%		−0.034	−0.72%		0.088	+2.10%		−0.282	+7.82%		−0.584	−12.12%	*
Insurance deductible (baseline: CHF 300)															
CHF 500 – 2 000	−0.134	−3.32%		−0.034	−0.72%		0.033	+0.78%		0.279	+12.53%		0.196	+4.59%	
CHF 2 500	−0.024	−0.61%		0.239	+4.79%		0.085	+2.01%		0.461	+14.07%	*	0.053	+1.19%	
Complementary insurance (baseline: No)															
Yes	0.008	+0.18%		0.445	+9.33%	**	−0.179	−4.36%		0.535	+14.69%	*	−0.391	−8.46%	**
Insurer's app (baseline: No)															
Yes	0.671	+16.47%	***	0.793	+17.63%	***	0.418	+9.46%		0.530	+14.65%	*	1.147	+27.88%	***
Constant	−0.074			−1.126		***	0.396		*	−1.334		***	−0.581		***
N	1 000			1 000			500			500			1 000		

Note: The significance levels are * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 6.8: Regression results for insurance factors

Sentiment factors Finally, our last set of variables included in the regression model in Table 6.9 exhibits the most significant correlations. Thereby, several variables are worth particular attention. The two first are curiosity and disease risk information. Whereas the logic behind genetic makeup, curiosity driving willingness to undergo a GT is sound, the result generated by the second (not significant) variable is intriguing. Indeed, our model suggests that it is the simple curiosity rather than any health-related considerations, captured by the disease risk information variable that drive the GT decision. This observation has already been made several times through our analysis with the health, and lifestyle variables, thus giving further confirmation. Moreover, the curiosity is self-based as it is only enough for GT itself and does not extend to willingness to share the results with the health insurer. Another pair of factors, however, present a pattern and they both display altruistic features. For the individuals stating that helping relatives or incentivize them to do a GT is a rather strong incentive for them to undergo one, they present different behaviors in certain cases. When the price is not yet displayed, in question A, or when it is the insurer who is the payer, in question C1, these incentives seem to differentiate respondents' choices. The effects range from 5.5% of increase in willingness to undergo a test in question A for helping relatives take better care of their health, to 22.4% for incentivizing a relative to undergo a test when the insurer pays for it. However, this altruism stops when individuals have to pay themselves. Ultimately, for those who could undergo a GT to incentivize relatives to do so, they are more likely to be willing to share these results with the health insurer.

Regarding deterrents, cost is an issue. The fear that the test is too costly especially arises when the price is displayed in question B. With strong significance, individuals for whom the cost may be a hurdle are 4.5% less likely to undergo the test in general and 5.6% when they are the sole payer. On the contrary, when it is the insurer who is supposed to pay for the test, respondents who had an issue with the expenditure are now 11.4% more likely to undergo the test once that burden is taken away. The last significant variable in this group of barriers is the lack of desire to know what potential disease one could have in the future. Not wanting to know correlates with a decrease in 7% in the overall willingness (question A) and of 14% when the insurer bears the cost. This correlation, nevertheless disappears in the last two regressions, question C1 and sharing willingness. Interestingly, fear of discrimination is not significant in our model, despite being fairly present in the literature (Cameron et al., 2009 or Dalpe et al., 2017 to name a few). Subsequently, we capture the outlook of our respondents on genetic testing and its future. We firstly note that those who agree or completely agree that GT will be common are distinguishable when price comes in question from those who did not. Their belief pushes them to perform the test when the price is displayed, giving an edge compared to those who do not believe so. Another belief – that the government will not be able to protect its citizens against negative aspects of genetic testing – has a significant impact. It translates into a decrease in willingness to do the test in models A and C1. Especially when the cost of the test is taken care of by the health insurer, the individuals who share this opinion are 8.4% less likely to undergo the test. Compelling enough, this attitude does not give a significant difference when it comes to deciding whether to share the data with the health insurer. Regarding that last question, the willingness to share anonymized data from the GT with the health insurer, respondents who agree that testing will be mandatory before being hired are 17.9% more likely to do so. Curiously, this perspective, though, does not make them more likely to perform the test. Finally, we study the usage of health-related applications. Firstly, the respondents who use health related apps for step counting, sleep cycle or women's health, for instance,have a higher propensity of accepting to undergo the test, except when they are the payers. This could be easily explained by the fact that these individuals are already familiar with health technologies and are willing to use them to monitor their health. However, these results hint again that this behavior is not driven by health considerations but rather by curiosity. This observation being backed up several times in our study is once again confirmed by the non-significance of the last usage of health-related apps for prevention factor. Regarding willingness to share data, these last two variables present conflicting results, suggesting that those who use health apps are more likely to share the anonymized data but using this app for prevention renders them less likely to do so.

Effect of the payer framing In this section, we document the effect of the health insurer as a payer framing on willingness to undergo testing as well as sharing the anonymized results with the health insurer, as outlined in Section 6.2.2 and Figure 7.1. We capture this effect by introducing an "insurer framing" dummy variable in the GTW regressions of question C and the SW of question D. To this aim, we firstly aggregate the data of questions C1 and C2, and we subsequently control for the framing by regressing the outcomes on the health insurer as a payer

Model	**A** – Baseline GTW			**B** – Price display			**C1** – Insurer payer			**C2** – Self payer			**D** – Data sharing		
	β_k	p_k	sig.	β_k	p_k	sig.	β_k	p_k	sig.	β_k	p_k	sig.	β_k	p_k	sig.
Is an incentive to undergo genetic testing (baseline: No)															
Curiosity	1.130	+18.92%	***	1.121	+15.77%	***	0.923	+19.38%	***	1.136	+19.14%	***	0.197	+3.15%	
Better health prevention	0.732	+10.88%	***	0.441	+4.83%	*	0.503	+9.72%		0.465	+6.35%		0.408	+6.90%	
Disease risk information	0.356	+4.66%		0.229	+2.30%		0.072	+1.28%		−0.097	−1.12%		−0.438	−5.63%	
Help relatives prevention	0.413	+5.51%	*	0.340	+3.58%		0.672	+13.47%	*	0.288	+3.70%		0.228	+3.67%	
Incentivize relatives	0.547	+7.65%	**	0.201	+1.99%		1.046	+22.37%	**	0.316	+4.09%		0.405	+6.85%	*
Is not an incentive to undergo genetic testing (baseline: No)															
Family finances	−0.027	−0.34%		−0.210	−1.82%		0.629	+12.49%	*	−0.221	−2.40%		0.262	+4.25%	
Family disapproves	0.129	+1.54%		0.239	+2.41%		−0.386	−5.79%		−0.268	−2.86%		0.273	+4.44%	
Fear test too costly	−0.059	−0.69%		−0.607	−4.46%	***	0.580	+11.41%	*	−0.593	−5.58%	*	−0.042	−0.60%	
Do not want to know	−0.837	−7.13%	***	−0.585	−4.33%	**	−1.343	−14.85%	***	−0.175	−1.94%		−0.073	−1.04%	
Induced lifestyle changes	0.236	+2.95%		0.234	+2.34%		0.560	+10.97%	*	−0.305	−3.20%		0.183	+2.91%	
Fear of discrimination	−0.365	−3.72%		0.198	+1.95%		0.005	+0.12%		0.116	+1.38%		−0.127	−1.79%	
Impact of genetic testing (baseline: No)															
Family discriminated ins.	0.034	+0.38%		−0.028	−0.29%		−0.470	−6.87%		0.225	+2.82%		−0.259	−3.52%	
Fewer illnesses, longer life	0.110	+1.30%		0.383	+4.10%	*	0.567	+11.11%	*	0.266	+3.39%		0.331	+5.49%	*
GT will be common	0.712	+10.52%	***	0.675	+8.09%	***	0.179	+3.23%		1.052	+17.34%	***	0.315	+5.20%	
GT to be hired	0.229	+2.85%		0.339	+3.56%		0.105	+1.87%		0.537	+7.54%		0.932	+17.96%	***
GT for insurance premiums	−0.309	−3.22%		−0.655	−4.72%	**	−0.026	−0.41%		−0.328	−3.42%		−0.357	−4.72%	*
Genetic passport for all	0.098	+1.14%		0.657	+7.82%	***	−0.223	−3.51%		0.592	+8.46%	*	0.257	+4.17%	
Segregation good/bad	0.172	+2.09%		0.174	+1.70%		−0.205	−3.23%		−0.129	−1.46%		−0.342	−4.54%	
Discrimination of disabled	−0.257	−2.73%		0.094	+0.87%		−0.270	−4.18%		−0.014	−0.20%		−0.246	−3.36%	
Government powerless	−0.702	−6.28%	***	−0.238	−2.40%		−0.600	−8.43%	*	−0.255	−2.74%		−0.070	−1.00%	
GT for infants	0.247	+3.11%		−0.087	−0.81%		−0.100	−1.61%		0.152	+1.84%		0.220	+ 3.54%	
GT for fœtuses	−0.275	−2.90%		−0.172	−1.52%		0.786	+16.10%	**	−0.281	−2.98%		−0.148	−2.08%	
Usage of health-related apps (baseline: No)															
Yes	0.784	+11.86%	***	0.509	+ 5.73%	*	0.644	+12.84%	*	0.021	+0.22%		0.620	+11.09%	**
Usage of health-related apps for prevention (baseline: No)															
Yes	0.166	+2.02%		0.322	+3.36%		0.087	+1.54%		0.318	+4.13%		−0.348	−4.60%	*
Constant	−1.868		***	−2.157		***	−1.292		***	−1.858		***	−1.501		***
N	1 000			1 000			500			500			1 000		

Note: The significance levels are * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 6.9: Regression results for sentiment factors

binary variable. By doing so, we witness a difference in outcome between the two groups, as suggested by the statistical analysis. The results of our regression in Table 6.10 corroborate with the observation made in the descriptive statistics analysis – the two framings present significantly different outcomes on the willingness to undergo a genetic testing. As the coefficient suggests, individuals who were told that it is the health insurer who should finance these GTs are 24.8% more likely to undergo the test, compared to individuals who would bear the cost of the test themselves. One can hypothesize that the insurer as a payer triggers more individuals to undergo the test because of the cost relief. To verify this conjecture, we run a subsidiary regression with the interaction term *Health insurer framing* × *Fear that test would be too costly*. When crossed with the health insurer as a payer variable, the fear of the test to be too costly is statistically significant with 90% confidence and has a coefficient of 0.724, thus validating the hypothesis that the health insurer as a payer alleviates the fear that the test may be too costly.

When moving to the SW, we as well witness a difference in outcome between both groups, as suggested by the statistical analysis. Our regression coefficient provides empirical evidence that individuals for whom the health insurer is the payer of the GT would be 9.18% more likely to share the test's anonymized data with the health insurer, when compared to individuals who are the sole payers of the GTs with 99% confidence. Making use of framings to carry another dimension into the analysis of GT and SW, we highlight the critical importance of the payer of these tests. From the findings in this framework emerges a new perspective in which the health insurer and the insured establish a collaboration relationship. When the health insurer pays for the GT to be undergone by the insured, which can lead to actionable information, this can be

viewed as an investment into the individual's health capital. In return, the insured shares the anonymized data. A possible explanation of this significantly different behaviour could be that it stems from a latent feeling of indebtedness towards the health insurer, rather than collaboration. However, it is not possible to determine the extent to which this might play a role in practice.

Model	**C** – GTW			**D** – Data sharing		
	β_k	p_k	sig.	β_k	p_k	sig.
Insurer framing (baseline: No)						
Yes	1.016	+24.81%	***	0.406	+9.18%	**
Constant	−0.585		***	−0.846		***
Observations	1,000					

Note: The significance levels are * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 6.10: Regression results for payer framing

6.4 Robustness checks and additional analysis

We now assess the robustness of our results by performing several checks. Firstly, in Table 6.11, we produce confusion matrices on 10 000 bootstrapped samples, providing the mean accuracy for the five models in regard to each variable of interest. The mean accuracies spread between 51% and 79%. The best performing model at explaining GTW is sentiment-related. Its accuracy ranges between 71% and 79%. Unsurprisingly, the model that performs the worst concerns political belief factors: there are no significant variables for this model. Finally, it is usually the willingness to share anonymized data with the health insurer that is best explained (model D).

Model	**A** – Baseline GTW	**B** – Price display	**C1** – Insurer payer	**C2** – Self payer	**D** – Data sharing
Socioeconomic	0.61	0.63	0.65	0.66	0.64
Insurance	0.55	0.63	0.60	0.65	0.69
Lifestyle	0.62	0.65	0.64	0.66	0.67
Political belief	0.51	0.62	0.60	0.65	0.67
Sentiment	0.79	0.76	0.79	0.76	0.71

Table 6.11: Prediction accuracy per regression model

6.4.1 Total regression, StepAIC and reduced form regression results

For the second robustness check, we calibrate several regression models to test the sensitivity of our coefficients. In a robust model, coefficients should almost not vary when new variables are introduced, a case that we simulate by running a regression making use of all our variables. Another aim of conducting a regression comprising all the variables is to subsequently reduce the model with a selection based on the AIC. This procedure keeps the variables that improve the explanatory power of the model and hence provide another mapping of variable importance in GT decision. In Table 6.12 we display both the total regression model and the reduced model. A first observation we can make regards the robustness of the coefficients. Expectedly, we can notice that coefficients of significant variables vary much less than those that are not significant. For instance, health, a variable that is not significant, has a coefficient that changes from 0.120

to −0.153 in the case of a reported good health. The factor curiosity, on the contrary, has a stable coefficient with only a minor change from 1.130 to 1.150 from the reduced to the total regression. Another interesting perspective is the change in the significance of the coefficients. Merging all the variables together has confirmed previous findings pointing at the importance of sentiment-related factors. Indeed, in the total regression, other sets of variables which displayed a few significant drivers in the separate models, lose their importance when merged together, leaving almost solely significance to the sentiment factors. Finally, if we take a closer look at the analysis of the data SW, we notice that two variables remain highly significant and bear a strong coefficient: having a health insurer's application and the insurer's framing (framing 2). The latter even displays a stronger coefficient, increasing from 0.409 to 0.575 while remaining significant at a 99% level of confidence. These findings confirm the importance of the relationship between the insurer and the respondent in the willingness to share anonymized GT's results. Using the same Table 6.12 but now looking at the coefficients of the reduced model, we have another evidence of the importance of sentiment variables as well as insurance-related ones. The variables remaining in the reduced models mostly come from the sentiment factors and for the SW decision variables, from the insurance factors.

6.4.2 Random forest

As a last analysis and robustness check for the importance of factors in the decision process of GTW or data sharing, we report results obtained from the random forest application.[3] In our case, we classify each respodent whether he/she is likely to undergo a GT, respectively to share the data or not. The algorithm performs the best classification and we extract the ranking of each variable is in Table 6.13 (see column "RF"). The variables considered as the most important are the ones that allow as soon as possible to classify the highest number of individuals into either group with the highest accuracy. We find that the first ranks stem from the incentive sentiments factors for GTW and for insurer's app usage and genetic testing impact for SW.

6.5 Conclusion and discussion

GTs by essence give access to personalized health care. Understanding what drives the decision to undergo these tests and the associated fears is crucial for PH-oriented policies. The twofold aim of this paper is reflected in the design of the ad-hoc survey. In order to fill the gap in the literature and better understand health-related decisions, we firstly analyzed the factors influencing genetic testing uptake as well as the sharing of the anonymized data from the GT with the health insurer. To do so, we ran regressions on five sets of variables susceptible to influence individuals' behavior regarding their GTW decision, including socioeconomic, insurance, lifestyle, political beliefs and sentiment factors. We find that mostly the insurance and sentiment factors present significant

[3] A random forest is composed of a multitude of decision trees, which are used as supervised categorisation algorithms. That is, for a decision tree, the data is provided to the machine which then tries to use the available variables to classify the "object" into either category.

Model	**A** – Baseline GTW		**B** – Price display		**C1** – Insurer payer		**C2** – Self payer		**D** – Data sharing	
	Total	Reduced	Total	Reduced	Total	Reduced	Total	Reduced	Total	Reduced
Gender (baseline: Male)										
Female	0.088		0.193		0.407		−0.179		−0.264	−0.324 *
Age (baseline: 35 – 44 years)										
25 – 34 years	0.021	0.041	0.081		0.369	0.297	0.496		0.032	
45 – 54 years	−0.224	−0.154	−0.178		−0.880 *	−0.877 *	0.216		0.010	
55 – 64 years	−0.626 *	−0.567 *	−0.194		−0.510					
Swiss nationality (baseline: No)										
Yes	−0.458 *	−0.487 *	−0.529 **	−0.555 **	−0.836 *	−0.782 *	−0.541	−0.509 *	−0.085	
Higher education (baseline: No)										
Yes	0.231		0.040		0.028		−0.317		−0.254	−0.229
Professional status (baseline: Full-time employed)										
Part-time	0.074	0.074	−0.127		−0.421		0.097		0.032	
Other	0.581 *	0.561 *	0.091		0.174		0.126		0.075	
Subjective wealth (baseline: Below average)										
Above average	0.251		0.209		0.040		0.885 **	0.657 **	−0.303	−0.250
Married (baseline: No)										
Yes	0.266	0.301	−0.077		−0.131		0.067		0.133	
Cancer history (baseline: No)										
Yes	0.266		−0.039		−0.277		−0.234		−0.123	
Health (baseline: Bad)										
Average	−0.038		0.214		0.755		0.332		0.294	0.458
Good	−0.153		0.246		0.023		0.100		−0.086	0.131
Region (baseline: French-speaking)										
German-speaking	0.047		0.495 *	0.507 **	−0.202		0.339		0.558 **	0.580 ***
Alcohol consumption (baseline: Everyday)										
Sometimes	0.055		0.306	0.327	0.054		−0.018		0.156	
Never	0.041		1.026 *	0.934 *	0.563		−0.199		0.461	
Cigarettes consumption (baseline: Everyday)										
Sometimes	0.655 **	0.627 **	0.063		0.169		−0.143		0.284	
Never	0.448 *	0.451 *	0.198		−0.660		0.301		−0.016	
Fruits and vegetables consumption (baseline: Everyday)										
Sometimes	0.338		15.473	14.815	15.171		0.322		−0.740	
Never	0.247		15.603	14.971	15.142		0.622		−0.651	
Sport at least once a week (baseline: No)										
Yes	0.215		−0.207		−0.400		−0.071		0.107	
Level of planning for the future										
	0.023		0.060		0.090		−0.011		0.041	
Level of loving taking risks										
	0.020		−0.005		0.121	0.095	−0.031		0.026	
Insurance plan (baseline: Family doctor)										
Standard	0.160		0.495 *	0.407 *	0.443		0.605		−0.310	−0.278
HMO	−0.350		−0.273	−0.261	−0.149		−0.099		0.095	0.128
CallMed	−0.254		−0.327	−0.299	−0.381		−0.367		−0.735 **	−0.760 **
Insurance deductible (baseline: CHF 300)										
CHF 500 – 2 000	−0.203		−0.047		0.072		0.469	0.519	0.190	
CHF 2 500	−0.084		0.274		0.022		0.780 *	0.566 *	0.134	
Complementary insurance (baseline: No)										
Yes	0.002		0.681 ***	0.680 ***	−0.131		0.613 *	0.419	−0.423 *	−0.447 **
Insurer's app (baseline: No)										
Yes	0.402	0.340	0.674 **	0.565 **	0.127		0.200		0.930 ***	1.043 ***
Insurer's framing (baseline: No)										
Yes									0.575 ***	0.549 ***
Is an incentive to undergo genetic testing (baseline: No)										
Curiosity	1.115 ***	1.126 ***	1.104 ***	1.200 ***	0.951 **	0.843 **	1.084 ***	1.211 ***	0.154	
Better health prevention	0.733 **	0.848 ***	0.392	0.553 **	0.418	0.575	0.680	0.501	0.505 *	0.419 *
Disease risk information	0.407	0.473 *	0.264		0.316		−0.022		−0.365	
Help relatives health prevention	0.410	0.418 *	0.350	0.496 **	0.556	0.686 *	0.438	0.423	0.096	
Incentivize relatives to undergo test	0.537 *	0.516 *	0.263		1.312 ***	1.175 ***	0.373		0.486 *	0.561 **
Is not an incentive to undergo genetic testing (baseline: No)										
Impact on family finances	−0.031		−0.203		0.779 *	0.691 *	−0.340		0.297	0.335 *
Family would disapprove	0.071		0.289		−0.553	−0.515	−0.280		0.200	
Test too costly	0.015		−0.594 **	−0.589 ***	0.615 *	0.583 *	−0.631 *	−0.740 **	−0.030	
Do not want to	−0.854 ***	−0.754 ***	−0.685 ***	−0.614 **	−1.364 ***	−1.429 ***	−0.250		−0.138	
Induced lifestyle changes	0.183		0.149		0.356	0.502	−0.432		0.142	
Fear of discrimination	−0.400	−0.429 *	0.309	0.350	0.136		0.303		−0.039	
Impact of genetic testing (baseline: No)										
Family discriminated for insurance	0.027		0.110		−0.749 *	−0.626 *	0.373		−0.224	
Fewer illnesses, longer life	0.058		0.311	0.348 *	0.715 *	0.707 **	0.055		0.401 *	0.439 **
Testing will be common	0.719 ***	0.807 ***	0.752 ***	0.800 ***	0.264		1.142 ***	0.918 ***	0.422 *	0.514 **
Testing mandatory to be hired	0.138		0.344		0.083		0.707	0.474	0.830 ***	0.861 ***
Testing for insurance premiums	−0.367	−0.312	−0.838 ***	−0.699 ***	−0.098		−0.435		−0.437 *	−0.460 *
Genetic passport for all	0.107		0.744 ***	0.680 ***	−0.353		0.837 **	0.656 *	0.183	
Segregation bad/good genomes	0.195		0.268		0.027		−0.106		−0.367	−0.358 *
Discrimination of handicaped	−0.255		0.010		−0.231		−0.137		−0.323	−0.347
Government not able to protect	−0.723 ***	−0.661 ***	−0.266		−0.393	−0.611 *	−0.382	−0.468	0.009	
Sequencing of infants genome	0.262	0.307	−0.102		−0.130		0.262		0.214	
Sequencing of fœtuses genome	−0.427 *	−0.377	−0.280		0.729 *	0.658 *	−0.500		−0.162	
Usage of health-related apps (baseline: No)										
Yes	0.737 **	0.929 ***	0.348	0.403	0.624	0.796 **	−0.092		0.510 *	0.431 *
Usage of health-related apps for prevention (baseline: No)										
Yes	0.273		0.409 *	0.385 *	0.316		0.407	0.368	−0.211	
Political interest (baseline: No)										
Yes	0.044		−0.026		0.132		−0.085		−0.039	
Belong to a political party (baseline: CHF 300)										
Yes	−0.249		0.007		−0.791 *	−0.662 *	−0.297		−0.062	
Political orientation (baseline: Left)										
	0.176		−0.431		1.740 **	1.413 *	−0.820	−0.827	0.223	
Constant	−2.784 *	−1.981 ***	−18.859	−17.768	−17.287	−1.449 *	−2.725	−2.206 ***	−1.759	−2.040 ***
N	1 000		1 000		500		500		1 000	

Note: The significance levels are * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 6.12: Regression results for the overall and reduced models

and strong results. These findings are corroborated by random forest modeling robustness checks. For instance, following a GT, an individual is 27.6% more likely to share the anonymized results

Model	**A** – Baseline GTW		**B** – Price display		**C1** – Insurer payer		**C2** – Self payer		**D** – Data sharing	
	Reduced	RF	Reduced	RF	Reduced	RF	Reduced	RF	Reduced	RF
Gender (baseline: Male)										
Female									✓	
Age (baseline: 35 – 44 years)										
25 – 34 years	✓				✓*	(10)				
45 – 54 years	✓				✓*	(10)				
55 – 64 years	✓*				✓	(10)				
Swiss nationality (baseline: No)										
Yes	✓*		✓**		✓*		✓*			
Higher education (baseline: No)										
Yes									✓	
Professional status (baseline: Full-time employed)										
Part-time	✓									
Other	✓*									
Subjective wealth (baseline: Below average)										
Above average							✓**	(10)	✓	
Married (baseline: No)										
Yes	✓									
Cancer history (baseline: No)										
Yes										
Health (baseline: Bad)										
Average									✓	
Good									✓	
Region (baseline: French-speaking)										
German-speaking			✓**						✓***	
Alcohol consumption (baseline: Everyday)										
Sometimes			✓							
Never			✓**							
Cigarettes consumption (baseline: Everyday)										
Sometimes	✓**									
Never	✓*									
Fruits and vegetables consumption (baseline: Everyday)										
Sometimes			✓							
Never			✓							
Sport at least once a week (baseline: No)										
Yes										
Level of planning for the future				(10)						
Level of loving taking risks					✓					
Insurance plan (baseline: Family doctor)										
Standard			✓*						✓	
HMO			✓						✓	
CallMed			✓						✓**	
Insurance deductible (baseline: CHF 300)										
CHF 500 – 2 000							✓			
CHF 2 500							✓*			
Complementary insurance (baseline: No)										
Yes			✓***				✓		✓**	
Insurer's app (baseline: No)										
Yes	✓		✓**				✓		✓***	(1)
Insurer's framing (baseline: No)										
Yes									✓***	
Is an incentive to undergo genetic testing (baseline: No)										
Curiosity	✓***	(1)	✓***	(1)	✓**	(2)	✓***	(1)		
Better health prevention	✓***	(2)	✓**	(2)	✓	(1)	✓	(2)	✓*	
Disease risk information	✓*	(3)		(3)		(3)		(5)		
Help relatives health prevention	✓*	(5)	✓**	(4)	✓*	(5)	✓	(4)		(7)
Incentivize relatives to undergo test	✓*	(4)		(6)	✓***	(4)			✓**	(6)
Is not an incentive to undergo genetic testing (baseline: No)										
Impact on family finances					✓*				✓*	
Family would disapprove					✓					
Test too costly			✓***		✓*		✓**	(9)		
Do not want to	✓***	(8)	✓**	(8)	✓***					
Induced lifestyle changes										
Fear of discrimination	✓*		✓							
Impact of genetic testing (baseline: No)										
Family discriminated for insurance					✓*					
Fewer illnesses, longer life		(9)		(8)	✓*	(7)	✓**	(7)	✓**	(3)
Testing will be common	✓***	(7)	✓***	(5)			✓***	(3)	✓**	(4)
Testing mandatory to be hired							✓		✓***	(2)
Testing for insurance premiums	✓		✓***						✓*	
Genetic passport for all			✓***	(7)			✓*	(8)		(9)
Segregation bad/good genomes									✓*	
Discrimination of handicaped									✓	
Government not able to protect	✓***				✓*		✓			
Sequencing of infants genome	✓									(5)
Sequencing of fœtuses genome	✓			(9)	✓*					
Usage of health-related apps (baseline: No)										
Yes	✓***	(6)	✓		✓**				✓*	
Usage of health-related apps for prevention (baseline: No)										
Yes		(10)	✓*	(9)		(6)	✓			(10)
Political interest (baseline: No)										
Yes										
Belong to a political party (baseline: CHF 300)										
Yes					✓*					
Political orientation (baseline: Left)										
					✓		✓			
N	1 000		1 000		500		500		1 000	

Note: The significance levels are * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 6.13: Regression results for the reduced model and comparison with the variable ranking from random forest modeling

with the health insurer if the individual already has an app from the insurer. Curiosity about one's genetic making is, overall, the strongest explanatory variable throughout all our models.

Respondents who stated that curiosity would for them be an incentive to undergo genetic testing are on average 18% more likely to undergo the test, disregarding the display of the price or the payer.

Subsequently, making use of framings in the design of our survey, we are able to shed light on the relationship between willingness to undergo a GT along with the related sharing and the nature of the payer of this GT, namely the individual itself or the health insurer. Our model is able to capture the critical importance of the payer in the decision process of undergoing the test and sharing anonymized genetic data. We provide empirical evidence of the impact of the health insurer as a payer on willingness to GTW and SW. Precisely, when the health insurer should be the payer, GTW and SW oncrease by 24.8% and 9.2% respectively.

The empirical results that this paper provides are relevant for several streams of research. On the academic side, we lay the ground for a deeper understanding of the presence of a payer on health decisions as well as sharing of health-related data. For insurance practitioners, we present the relevance of collaboration between clients and their insurance. An interesting topic may be, for example, how the amount of the coverage of genetic testing influences preferences. However, while we believe that our set of variables is quite extensive, further uncaptured idiosyncratic characteristics may play a role in the decision process. We conducted our research on survey-collected data, which intrinsically carries several biases. Self-reported data includes flaws such as social desirability (see Gittelman et al., 2015) or health specific biases (documented in Bound et al., 2001). Hence, results are to be taken with hindsight and a robustness test on another type of data (such as panel data, to get rid of confounding variables) could improve the results. To put these results in the light of the recent pandemic, we repeated the survey to understand whether there is a shift in behavior, in another working paper (Deruelle et al., 2022). Indeed, during the Covid-19 pandemic, society was collectively gathering and sharing health information in order to find a cure. Frequent access to Covid-19 antigenic tests, possibility to self-administer covid-related tests and the vaccine found via the genetic research of the virus have changed the way individuals perceive health-related data and new medical technologies. At the individual level, this translated in an increase of willingness to use and share genetic-related data, and more specifically, direct-to-consumer GT. Finally, the results we obtain are valid for Switzerland or countries under the same health care system. Extending this research to other models of health care would further increase the knowledge on health decisions.

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Chapter 7

Designing Privacy in Personalized Health: An Empirical Analysis

Abstract: We analyze individuals' preferences regarding how they want to store their personal health data. Secure storage of personal health data is of paramount importance to convince citizens to use personal health technologies. We use data from a survey experiment fielded in Switzerland in March 2020 and perform regression analyses on a representative sample of Swiss citizens in the French- and German-speaking cantons. Survey data yield information regarding the extent to which individuals are likely to use two personalized health technologies, namely, health "apps" and direct-to-consumer genetic tests depending on storage conditions. The data shows that respondents are more likely to use both apps and tests if they can store the data themselves. The relationship is stronger for app usage than for tests, which can be explained by the stigma and relatively more intrusive nature inherent to genetic testing. Our results demonstrate that concerns regarding data protection trumps any other variables when it comes to the willingness to use personalized health technologies. Individuals prefer a data storage format where they retain control over the data. Ultimately, this study presents results susceptible to inform decision-makers on how the settings under which data is stored affects citizens' willingness to produce personal health data.

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7.1 Introduction

Personalized health is based on the massive integration of biomedical and social data into research to determine how individuals' physical and social environments, genetic endowments and behaviors influence their health (Barazzetti et al., 2021). This data helps to customize preventive and therapeutic interventions to the individual genetic and clinical characteristics of each patient (Minvielle et al., 2014). For example, data from genetic tests (Phillips et al., 2018) can be used to develop personalized treatment for cancer patients and to create personalized plans for health prevention. Other personal health technologies can be used directly by individuals, such as health trackers and apps, to generate large amounts of individual health data and monitor their own health.

With the generation of large amounts of personalized health data, the health industry has taken a keen interest in making use of this data. A crucial challenge for the future of personalized health is thus the handling of patients' data and specifically the protection of their privacy. Without patients' willingness to rely on personalized health technologies and create data, the potential collective benefits of personalized health (Prainsack, 2014) are out of reach. In this context, privacy and data protection are critical problems that need to be addressed by policymakers and practitioners (Ostherr et al., 2017; Vayena et al., 2018; Jacobs and Popma, 2019), if they want patients to produce and store the data in the first place. Moreover, privacy protection is important because personalized health bears the risk of discrimination amongst individuals based on genetic profiles (Feldman, 2012; Lee, 2015; Phillips et al., 2014), as well as because powerful economic interests are likely to take advantage of citizens' cognitive biases and weak data protection legislation to access to personal health data (Boyd and Hargittai, 2010; Brown, 2016). Addressing public preferences regarding storage and data privacy is thus a prerequisite for patients to produce data, even before it can be shared for the purpose of research (Blasimme et al., 2019).

Previous research (Whiddett et al., 2006; Laurie, 2011; Caenazzo et al., 2015; Patil et al., 2016; Persaud and Bonham, 2018; Bühler et al., 2019; Trein and Wagner, 2021) has shown that individuals are not willing to have their personal information shared beyond the purpose of clinical care and prefer to be consulted before their information is released. Yet, recent studies demonstrate broad public support for the use of health data for the purpose of research (Garrison et al., 2016; Stockdale et al., 2018; Braunack-Mayer et al., 2021). Empirical research has also shown that individuals are willing to share their genetic data, especially with doctors and for non-profit causes compared to for profit activities (Middleton et al., 2020). Furthermore, information about who benefits from genetic data and the option to withdraw access to data increases the likelihood of genetic data sharing (Milne et al., 2021).

Our paper acknowledges these insights from critical privacy research and takes an empirical approach to explore the design of privacy regarding the storage of health data. In this article, we build on this research to analyze individual support for different privacy designs for data

storage in personalized health. We look beyond precision medicine focused on sick patients and zoom-in on the prevention-oriented dimension of personalized health (Khoury et al., 2016). We ask: what are individuals' preferences regarding how they want to store the personal health data they opt to produce? To respond to this research question, we focus on two voluntary methods of data generation which cover the medical and the non-medical dimensions of personalized health: blood and genetic tests (Phillips et al., 2018) and health apps (Allen and Christie, 2016). We thus look at a form of personalized health data that is produced by users themselves. We analyze the support for two storage options which both guarantee that data can be shared for the purpose of research. The first one is "private" storage, i.e. which control is entirely up to the user. This is the case for instance in Switzerland with the Electronic Health Record: the patient can access his health records, while third party access requires explicit authorization by the patient (DePietro et al., 2015). The second one is "common" storage in which users' data contributes to enriching a common database and would not require explicit patient's authorization for authorized third party access such as healthcare professionals and possibly researchers.

7.2 Research Design

We analyze this question using a survey experiment fielded in Switzerland in March 2020. Switzerland provides a relevant context as the country has a health care system, which puts the responsibility for health care on individuals (DePietro et al., 2015; De Pietro and Francetic, 2018), who in turn need to make informed choices regarding their personal health. In Switzerland, the emergence of personalized health is the result of national and cantonal initiatives in building infrastructures for the integration of personalized health data in health care (Barazzetti et al., 2021). In other words, Switzerland is a "consumer-driven" healthcare system (Okma and Crivelli, 2013) and as such, citizens' willingness to use personalized health technologies is highly relevant. Furthermore, Switzerland is a rather typical case concerning public support for genetic data sharing (Middleton et al., 2020; Milne et al., 2021).

Our analysis proceeds in two steps. Firstly, we analyze whether citizens are more likely to use health apps and conduct a genetic test if they could store the data themselves or if it is stored by public authority. Secondly, we assess the role of background variables to explain potential differences in citizens' preferences regarding storage. The results of our analysis show that if storage is "private", individuals are more likely to use health apps and do tests. Other surveyed variables are not significant: those who have a right rather than left political orientation are not more willing to share their data compared to those with a left political orientation. The same is true for those who believe that it is the role of the state to collect and store data. Bad health and reports having genetically inherited diseases do not lead individuals to more or less willingness to share their personal health data. These findings underline that a major challenge for implementing personalized health technology is to create legitimacy for new technologies.

At the core of our analysis, we test respondents' willingness to generate personalized health

data depending on storage conditions. To test the robustness of our results, we explore a set of explanatory/background variables on respondents' views on the role of the state on health and welfare beyond the issue of storage and two sets of alternative explanations: respondents' health and socioeconomic variables.

Respondents' views on the role of the state in health and welfare indicates whether individuals are supportive of state intervention in these areas. The first two background variables are the respondents' views on whether it is the role of the state to provide social security and their views on whether it is the role of the state to reduce economic inequalities. These two variables are useful to paint big strokes on the role of the state: if individuals are largely in favour of state involvement in these aspects but adverse to have their data stored by the state, this would indicate that this is more likely due to privacy concerns rather than political views on the role of the state. If individuals are adverse to both, it would mitigate our findings and indicate that political views are significant.

Regarding the role of the state, we add two other background variables: the respondents' views on whether it is the role of the state to store and use data and their views on whether it is the role of the state to regulate storage and sharing data. In contrast to the first two variables, if respondents say that it is indeed the role of the state and are willing to have their data stored by the state, this would indicate that political views and personal choice are coherent in explaining individuals willingness to use personalized health technology.

Turning to alternative explanations we look into four socio-economic variables, namely, age, subjective wealth, education level and language region (as per the specificity of the case of Switzerland). The goal is to investigate whether there are disparities between those who anticipate potential health problems in the near future and those who do not (age variable), those who can afford to invest in alternative storage solutions that match their preferences and those who do not (wealth variable), those who have better understanding of privacy and storage issues than others (education) and finally whether there are cultural disparities between the German- and French-speaking respondents in Switzerland.

Finally, focusing on health specifically we look into individuals' relationships with their own health. We survey their self-assessed health conditions and whether respondents have family antecedents of cancer. The role of those variables is to identify whether health conscientious individuals are more likely to want to monitor their health using apps or genetic tests.

7.3 Survey and Results

The data set for our analysis stems from an online survey that was fielded in March 2020 as part of a larger project on health policy and genetic data. It is a sample ($N = 1\,000$) of the Swiss population that is representative according to the following categories: men and women are distributed equally and the participants, aged between 25 and 65 years, are evenly distributed

into four age groups. Furthermore, two thirds (67%) of the sample is comprised of Swiss Germans and the remaining 33% hail from Switzerland's French-speaking region. The latter approximate the Swiss population along the two largest language regions. We do not consider the Italian- nor the Romansh-speaking regions since they correspond to only around 8% respectively less than 1 percent of the population. In a sample of 1 000 respondents, these regions would yield only a small number of answers with limited statistical power to draw inferences.

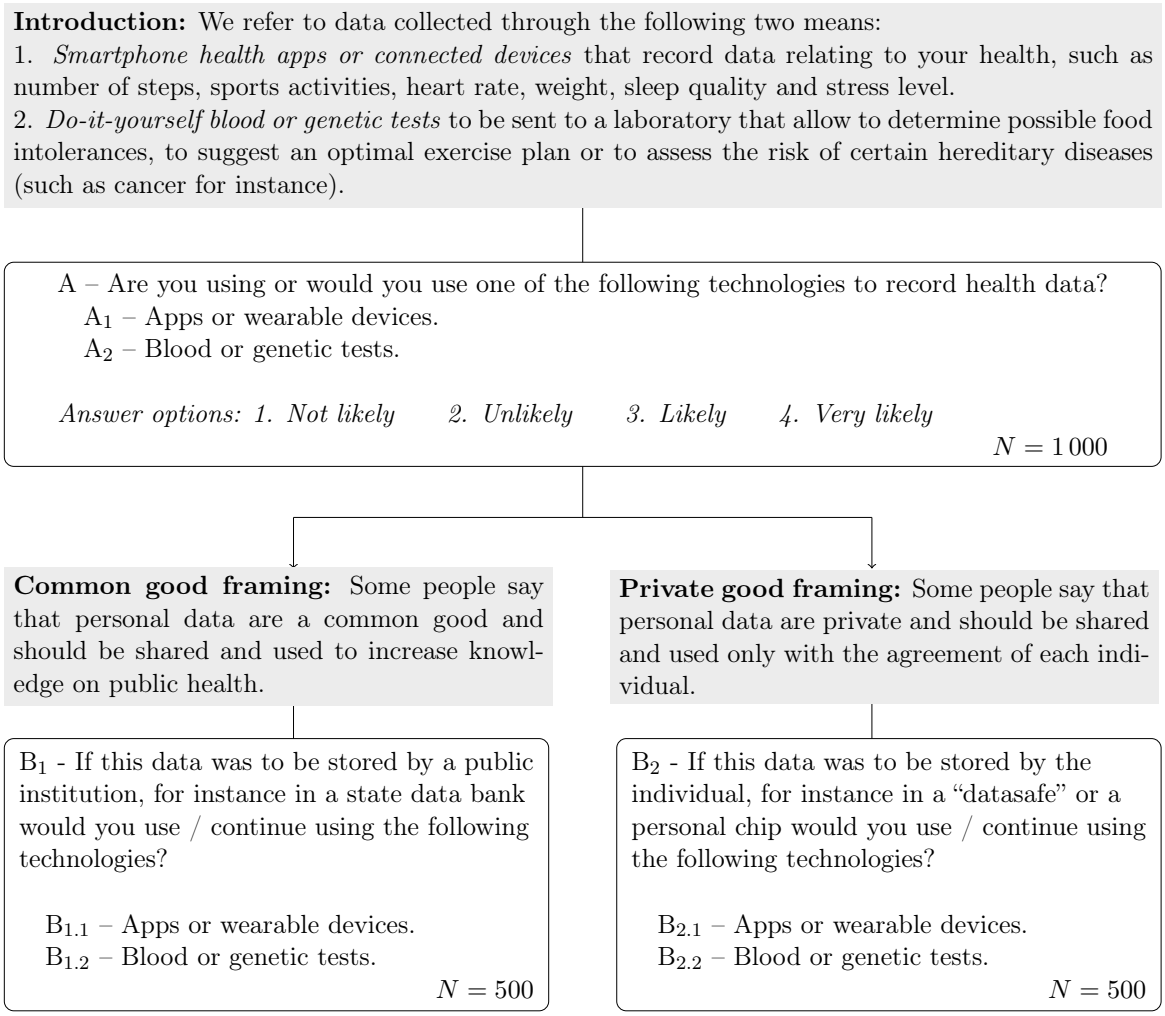
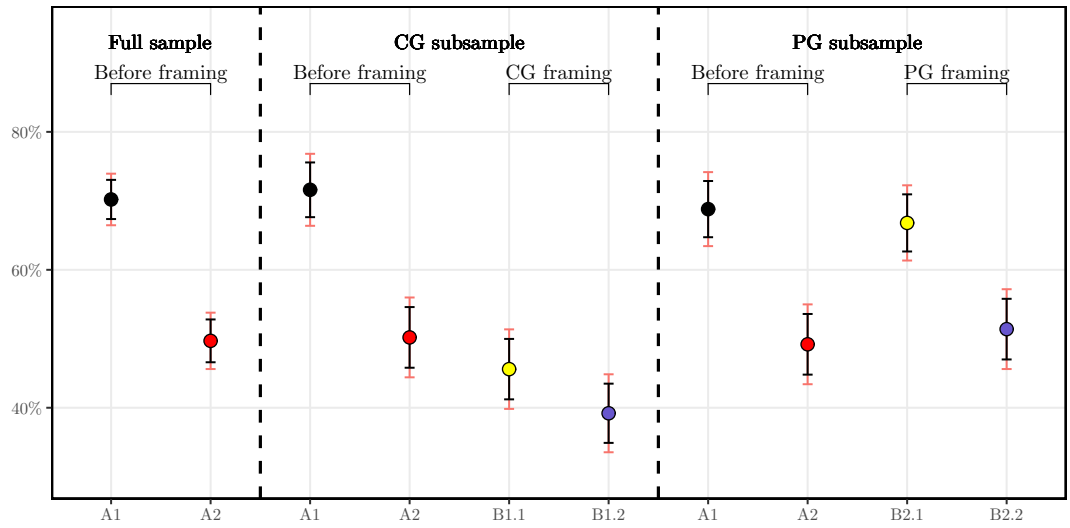


Figure 7.1: Operationalization of the hypothesis in the survey.

In the survey, after briefly explaining what is meant by apps and tests, we firstly ask respondents how likely it is that they will use health related apps (question A_1) or tests (question A_2). After that, we randomly frame individuals into two equal-sized groups while controlling for the gender, age and language region distributions. One group (common good framing) received the information that some claim that individual health data should be shared with the state (e.g., as a common good). Then we asked them how likely it is that they still use apps (question $B_{1.1}$) or tests (question $B_{1.2}$). The other group (private good framing) was provided with the information that some claim that personal health data should be stored under personal control. Again, this group was asked how likely it is they will use an app (question $B_{2.1}$) or test (question $B_{2.2}$). We illustrate the survey setup in Figure 7.1.



The abbreviations "CG" and "PG" stand for common good respectively private good. The results of the "Before framing" panel are based on $N = 1\,000$ observations while those of the "CG framing" and "PG framing" are based on $N = 500$ observations. Confidence intervals are at the 95% and 99% levels.

Figure 7.2: Levels of willingness to use apps and make tests along the framing.

For each question laid out in Figure 7.1, our statistics report the share (in percent) of those who responded "likely" or "very likely". Our first results are depicted in Figure 7.2 and illustrate the impact of the framing. The three panels of the graph show the share of respondents that are willing to use apps and make tests, initially (before framing), and in both the common and private good framings (using a subsample of observations). In the second and third panels, we report the willingness to use apps and tests for the subsample before framing (results are in line with those of the whole sample given in the first panel) before indicating the results using the framing. First, we observe that individuals are much less likely to do genetic tests (49.7 percent) than to use apps (70.2 percent). Further, we find that those who received the information that data might be stored with the state (CG framing) are less likely to use apps (45.6 percent) and even less likely to conduct genetic tests (39.2 percent) compared to those who received the information that data should be stored with the individual (PG framing). In the latter case, the willingness to use is slightly higher (66.8 percent for apps and 51.4 percent for tests) when compared to the situation before framing.

In addition, we ask further questions to measure the different aspects that we discuss above. Concerning socioeconomic variables, we include the gender, age, citizenship, education level, professional status, subjective wealth, marital status, language region, subjective health, and cancer history in the family of the respondent. Furthermore, we operationalize political background variables. We ask participants whether it is the role of the state to provide social security, to reduce economic inequalities, to store and use data as well as to regulate the storage and sharing of data.

In Table 7.1, we illustrate the respondents' willingness to use health-related apps or to participate in genetic testing along the different explanatory variables in the different framing setups. Again,

and across the variables, we observe that individuals are much less likely to do genetic tests than to use apps. For example, both men and women are similarly likely to use apps (70.6 respectively 69.8 percent) but for both genders, the willingness to use tests is lower (51.2 respectively 48.2 percent).

	Before framing				CG framing		PG framing			Before framing				CG framing		PG framing	
	N	(share)	A_1	A_2	$B_{1.1}$	$B_{1.2}$	$B_{2.1}$	$B_{2.2}$		N	(share)	A_1	A_2	$B_{1.1}$	$B_{1.2}$	$B_{2.1}$	$B_{2.2}$
Socioeconomic factors									**Language region**								
Gender									French	330	(33.0)	72.4	53.9	48.5	41.8	67.3	55.8
Male	500	(50.0)	70.6	51.2	44.8	40.4	69.2	56.4	German	670	(67.0)	69.1	47.6	44.2	37.9	66.6	49.3
Female	500	(50.0)	69.8	48.2	46.4	38.0	64.4	46.4	**Subjective health**								
Age									Bad	75	(7.5)	60.0	52.0	47.1	44.1	56.1	48.8
25 – 34	250	(25.0)	78.4	51.2	41.1	35.5	69.8	52.4	Fair	337	(33.7)	71.5	48.4	46.6	38.0	64.4	49.4
35 – 44	250	(25.0)	72.4	54.8	46.0	40.5	74.2	60.5	Good	588	(58.8)	70.7	50.2	44.9	39.3	69.8	53.0
45 – 54	250	(25.0)	67.2	47.6	52.4	43.7	66.1	49.2	**Cancer in family history**								
55 – 65	250	(25.0)	62.8	45.2	42.7	37.1	57.1	43.7	No	540	(54.0)	69.4	47.4	47.4	40.4	66.7	49.6
Swiss nationality									Yes	460	(46.0)	71.1	52.4	43.5	37.8	67.0	53.5
No	255	(25.5)	75.3	58.4	51.3	47.9	73.9	60.9	*Political factors*								
Yes	745	(74.5)	68.5	46.7	43.9	36.6	64.1	47.8	**Role of the state**								
Higher education									Provide social security								
No	613	(61.3)	66.2	47.3	45.5	37.8	63.8	52.8	No	386	(38.6)	68.7	50.5	42.2	37.2	69.5	52.9
Yes	387	(38.7)	76.5	53.5	45.7	41.5	71.4	49.2	Yes	614	(61.4)	71.2	49.2	47.8	40.5	65.2	50.5
Professional status									Reduce economic inequalities								
Full-time	516	(51.6)	72.9	51.4	49.0	41.7	68.5	53.3	No	386	(38.6)	70.2	48.4	37.8	31.9	66.7	51.7
Part-time	278	(27.8)	69.1	42.1	43.7	34.1	61.5	37.8	Yes	614	(61.4)	70.2	50.5	50.2	43.5	66.9	51.2
Other	206	(20.6)	65.0	55.8	39.6	39.6	70.0	66.0	Store and use data								
Subjective wealth									No	783	(78.3)	67.2	45.7	41.8	33.8	62.8	46.3
Below avg.	589	(58.9)	68.3	51.8	43.4	38.5	61.4	50.2	Yes	217	(21.7)	81.1	64.1	58.9	58.0	81.9	70.5
Above avg.	411	(41.1)	73.0	46.7	48.6	40.2	75.1	53.3	Regulate storage and sharing of data								
Marital status									No	533	(53.3)	67.2	47.8	40.2	34.6	64.5	49.8
Married	478	(47.8)	71.5	48.3	48.5	36.9	62.9	47.3	Yes	467	(46.7)	73.7	51.8	51.2	43.9	69.7	53.4
Other	522	(52.2)	69.0	51.0	42.9	41.3	70.3	55.1									

The abbreviations "CG" and "PG" stand for common good respectively private good. The column "N" denotes the number of respondents. The share of respondents and the level of agreement (share of answers "likely" and "very likely") in each question are expressed in percent. Results for the CG and PG framing are based on a total $N = 500$ observations.

Table 7.1: Levels of willingness to use apps and make tests.

Concerning political factors, we transformed the variables that measure the individual's level of usage in the four statements into binary measures (yes/no). In the original survey, the variables measure the statements on a five-point Likert scale, from "do not agree" to "fully agree", allowing for an "undecided" category. To simplify the presentation of the results and our econometric analysis, we have coded both disagreement categories as well as the "undecided" category as a "no" since we aim to distinguish actual willingness. Indeed, we observe that the political factors seem to make a difference regarding the willingness to use apps and conduct tests. Notably, those who feel that it is the role of the state to store and use data are more likely to use apps and tests. Finally, let us note that we have also coded the variable regarding subjective health, combining the categories "bad" and "very bad" as well as "good" and "very good" into "bad" and "good" respectively. Further, we have changed the education level variable into a binary variable classifying individuals into those who at least have a high school diploma and those who have not.

To understand deeper how the usage of apps and tests is linked to the different explanatory variables, we estimated different linear regression models. Specifically, we built four regression models using the binary answer variable (see above) for the likelihood to use an app or to conduct

	Apps and wearable devices						Blood and genetic tests					
	(1) Question A_1			(2) Question $B_{x.1}$			(3) Question A_2			(4) Question $B_{x.2}$		
	Coeff.	Marg. eff.	Sig.	Coeff.	Marg. eff.	Sig.	Coeff.	Marg. eff.	Sig.	Coeff.	Marg. eff.	Sig.
Gender												
Female	0.081	+1.99%		0.022	+0.57%		−0.068	−1.66%		−0.196	−4.88%	
Age (baseline: 35 – 44)												
25 – 34	0.309	+7.27%		−0.151	−3.44%		−0.101	−2.44%		−0.157	−3.93%	
45 – 54	−0.244	−5.97%		0.038	+0.96%		−0.295	−7.24%		−0.105	−2.65%	
55 – 65	−0.365	−9.01%		−0.345	−7.68%		−0.332	−8.17%		−0.349	−8.55%	
Swiss nationality												
Yes	−0.180	−4.38%		−0.257	−5.80%		−0.370	−9.14%	*	−0.394	−9.60%	*
Higher education												
Yes	0.386	+8.99%	*	0.009	+0.26%		0.308	+7.11%	*	−0.070	−1.78%	
Professional status (baseline: Full-time)												
Part-time	−0.166	−4.04%		−0.225	−5.10%		−0.379	−9.35%	*	−0.422	−10.26%	*
Other	−0.286	−7.03%		−0.086	−1.96%		0.146	+3.45%		0.251	+6.22%	
Subjective wealth above average												
Yes	0.139	+3.37%		0.424	+10.43%	**	−0.303	−7.44%	*	0.111	+2.72%	
Married or partnership												
Yes	−0.041	−0.97%		−0.016	−0.33%		0.154	+3.63%		0.220	+5.45%	
German-speaking region												
Yes	−0.114	−2.76%		0.003	+0.12%		−0.095	−2.30%		−0.050	−1.30%	
Subjective health (baseline: Bad)												
Fair	0.472	+10.83%		0.209	+5.09%		−0.042	−1.03%		0.046	+1.10%	
Good	0.379	+8.83%		0.197	+4.81%		0.068	+1.61%		0.121	+2.98%	
Cancer in family history												
Yes	0.147	+3.54%		−0.065	−1.46%		0.285	+6.60%	*	0.073	+1.77%	
Role of the state (baseline: No)												
Provide social security	0.160	+3.86%		−0.112	−2.55%		−0.172	−4.20%		−0.142	−3.56%	
Reduce economic inequalities	−0.132	−3.20%		0.270	+6.60%		0.069	+1.63%		0.221	+5.48%	
Store and use data	0.747	+16.32%	***	0.768	+19.00%	***	0.710	+15.34%	***	0.973	+23.12%	***
Regulate storage and sharing of data	0.033	+0.83%		0.094	+2.30%		−0.073	−1.78%		−0.036	−0.95%	
Private good framing												
				0.963	+23.67%	***				0.558	+13.74%	***
Constant	0.353			-0.483			0.401			-0.134		
N	1,000			1,000			1,000			1,000		

Note: The significance levels are * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 7.2: Regression results for the apps and tests usage.

a test. We use logit models because they yield the lowest Akaike Information Criterion (AIC) values compared to models with a probit or a cloglog link function. As robustness tests, we also estimated models where we used, for example, continuous instead of binary measures for the political variables, which does not yield different results. These findings are available upon request from the authors.

We estimate two models regarding the likelihood to use apps and two models concerning the usage of tests. In both cases, we estimate one reference model with the explanatory variables based on the initial question A_1 respectively A_2 (before framing). The second model uses the response variable where participants were framed regarding the storage of their data (Table 7.2).

The results of the regression models show that very few socioeconomic variables are statistically significant (see reference models 1 and 3 in Table 7.2). Regarding the use of apps, only those reporting to have a higher level of education are almost 9 percent more likely to use apps. Among political factors, we see that respondents who feel that it is the role of the state to store and use data are more than 16 percent more likely to report app usage.

Regarding the use of genetic tests, the reference model indicates that respondents with at least a high-school diploma and a family history of cancer are more likely to engage in tests compared to those who have a lower level of education and no cancer history in their family. Furthermore, Swiss citizens and those who only work part-time are less likely to take such tests. Concerning political factors, the results indicate that those who believe that the state should store and use

individual data are more likely to do such tests by more than 15 percent.

In the second set of regression models (models 2 and 4 in Table 7.2), a binary variable indicates if the respondent received the private good framing instead of the baseline common good framing (Figure 7.1). Our results show that such a framing significantly increases the likelihood to use apps and wearable devices by almost 24 percent and makes it almost 14 percent more likely that individuals do blood and genetic tests.

These results underline the importance of data protection when it comes to implementing practices of personalized health. Individuals' control over their own data is important when it comes to using health-related apps and tests; more so than beliefs about subjective health and a family history of cancer.

7.4 Conclusions

As per research expectations, this study shows that individuals are more likely to use personalized health technologies if their data are kept on "private" storage which grants control to the user rather than "common" storage wherein user's control is nil (Ostherr et al., 2017; Vayena et al., 2018; Jacobs and Popma, 2019). Other explanatory variables have a less clear effect. For instance, respondents with a degree in higher education are more likely to use those technologies. However, this increased likelihood disappears once the framing of data as "common good" is introduced, showing that privacy concerns remain the crux of storage issues.

Nevertheless, ideological views should not be completely eschewed: indeed, those who believe that it is the role of the state to collect and store data are more likely to use personalized health technologies. Considering that respondents' willingness to use health technologies is significantly higher when the state is not involved and health data is considered a private good, more research should be done on the role of political factors on citizens' likelihood to use health technologies. Future research could, for instance, explore whether citizens and patients are more likely to use health apps, where their personalized health data are handled by a private third party, such as their private insurance, rather than by the state.

On the political front, there is much to be done in order to incite a more widespread use of personalized health technologies. Overall, the major challenge for implementing personalized health technology is to create legitimacy by offering safe storage conditions. Personalized health data is no different than other forms of personal data: mitigating data protection concerns is of the utmost importance for a correct implementation of personalized health objectives. In other words, if users retain control, the design of data privacy is likely to be perceived as more legitimate.

The are important differences between health apps and genetic tests. The likelihood for respondents to self-perform a direct-to-customer test is, regardless of the framing, lower than for

health apps. It is also lower throughout all background variables. This can be explained by the stigma and relatively more intrusive nature inherent to genetic testing. Ultimately, this means that self-performed genetic tests, as a specific form of personalized health technology need to be legitimized by maintaining individual control over health data.

Some of our results indicate where public authorities might want to focus their efforts. This is the case, for example, with regard to respondents' level of education: those with higher education are around 9% more likely to use apps and 7% more likely to use tests than those with no higher education. This discrepancy should be researched further, as it may reflect a socioeconomic divide: apps rely on connected devices that not everyone can prioritize to purchase. This is supported by the fact that our respondents with a subjective wealth above average are more than 10 percent more likely to use apps. This could also be reflective of data science literacy. In sum, it is particularly important for public authorities wanting to increase personalized health technologies usage to target groups identified along these variables. Potentially, this could include improving scientific literacy and educating on the personal and collective benefits of producing this data.

Like any other research, our study comes with limitations. The first one being the generalization of our findings. Switzerland is arguably at the forefront of the personalized health "turn" and thus the debate regarding data protection is particularly relevant, unlike in other national contexts in Europe or worldwide. Second, our study is limited to personalized health technologies (smartphone apps, wearable devices, do-it-yourself tests) where data generation is depending on the patients' willingness to use them. Our results are therefore not relevant to personalized health data generated as a result of a medical intervention. Future research could focus on comparing preferences between personalized health technologies used on a voluntary basis as opposed to personalized data produced in a medical context. It would shed light on whether the way data is generated changes preferences regarding storage. Furthermore, the scope of our empirical analysis is limited as we could not include the Italian-speaking population of Switzerland.

Despite these potential limitations, our study contributes to our understanding of privacy in personalized health. The results underline in a powerful way that a solid majority of citizens want to remain in control of their personalized health data. Therefore, in order to promote the production of personalized health, decision makers should create storage solutions that emulate the Electronic Health Record which allow citizens to give consent for the use of their data for the purpose of research.

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Appendix A

Survey questions

Question A1: Gender. What is your gender? *Answer options: male; female.*

Question A2: Age. What is your age? *Numeric answer.*

Question A3: Region. What is the postal code of your main residence? *Numeric answer.*

Usage, storage and sharing of data

In the following questions, we refer to two types of data collected through the different means below:

Smartphone health apps or connected devices that record data relating to your health, such as number of steps, sports activities, heart rate, weight, sleep quality or stress level.

Do-it-yourself blood or genetic tests to be sent to a laboratory to determine possible food intolerances, to suggest an optimal exercise plan or to assess the risk of certain hereditary diseases (such as cancer, for example).

Question B1: Technologies usage. Do you or would you use the technologies below to record your data?
1. Apps or connected devices
2. Blood or genetic tests
Answer options: not likely; unlikely; likely; very likely.

Question B2-: Possible reasons of refusal of usage of apps or connected devices usage. *(Only if answered* not likely; unlikely *in question B1.1.)* You have indicated that you rather do not want to use connected applications or devices. What are the reasons? Several answers are possible. *Answer options: lack of utility; lack of time; data protection concerns; too expensive; other.*

Question B2+: Possible reasons of acceptance of usage of apps or connected devices usage. *(Only if answered* likely; very likely *in question B1.1.)* You have indicated that you rather want to use connected applications or devices. What are the reasons? Several answers are possible. *Answer options: curiosity; surveillance; coaching sport / health; too expensive; other.*

Question B3-: Possible reasons of refusal of usage of blood or genetic tests. *(Only if answered* not likely; unlikely *in question B1.2.)* You have indicated that you rather do not want to use connected applications or devices. What are the reasons? Several answers are possible. *Answer options: lack of utility; lack of time; data protection concerns; too expensive; other.*

Question B3+: Possible reasons of acceptance of usage of blood or genetic tests. *(Only if answered* likely; very likely *in question B1.2.)* You have indicated that you rather want to use connected applications or devices. What are the reasons? Several answers are possible. *Answer options: curiosity; surveillance; coaching sport / health; too expensive; other.*

Framing for storage and sharing of data.
Framing A Some say that recorded personal data is a common good and should be shared and used to improve public health knowledge.

Question B4a: Storage. If this data were to be stored by a public institution, for example in a state database, would you use / would you continue to use the technologies below?
1. Apps or connected devices
2. Blood or genetic tests
Answer options: not likely; unlikely; likely; very likely.

Question B5a: Sharing. If this data were to be anonymized by the state and used for research, would you use / would you continue to use the technologies below?
1. Apps or connected devices
2. Blood or genetic tests
Answer options: not likely; unlikely; likely; very likely.

Framing B Some say that stored personal data is private and should be shared and used only with the consent of each individual.

Question B4b: Storage. If this data were to be stored by the individual, for example in a personal "datasafe" or chip, would you use / continue to use the technologies below?
1. Apps or connected devices

2. Blood or genetic tests
Answer options: not likely; unlikely; likely; very likely.

Question B5b: Sharing. If this data were to be accessible only by the individual, would you use / would you continue to use the technologies below?
1. Apps or connected devices
2. Blood or genetic tests
Answer options: not likely; unlikely; likely; very likely.

Question B6: Sharing. Whom would you be willing to share your anonymized data with?
1. Apps or connected devices
2. Blood or genetic tests
Answer options: my family & friends; my social media; my doctor; a patient network; my health insurer; my employer; a state-owned datasafe; a pharmaceutical company (Novartis, Roche, etc.); a technological company (Apple, Google, Fitbit, etc.); university researchers.

Genetic Tests

Introductory paragraph

For the following questions, we focus on **genetic testing**. Some of these tests determine the risk for hereditary diseases, for instance breast cancer for women and prostate cancer for men. These tests can then be used to plan the frequency of preventive medical examinations (e.g. mammograms) or to improve lifestyle (diet, physical activity) in order to decrease or postpone the risk of disease.

Question C1: Incentives to undergo genetic testing. Which of the following reasons might incentivize you to take a genetic test? For each reason, indicate your level of agreement. In random order:
1. I am curious about my genetic makeup.
2. My results could help me to take better care of my health.
3. My results could help my relatives to take better care of their health.
4. It could incentivize my relatives to undergo a genetic testing for themselves.
5. My results could provide me useful information about hereditary diseases or my cancer risks.
Answer options: five levels from strongly disagree *to* totally agree.

Question C2: Reasons not to undergo genetic testing. Which of the following reasons might incentivize you to take a genetic test? For each reason, indicate your level of agreement. In random order:

1. I fear a possible discrimination.
2. I fear that the test would be too expensive.
3. Some members of my family could disapprove me taking a test.
4. Knowing my cancer risk may force me to lead a different lifestyle.
5. I don't want to know what potential illness I might have in the future.
6. I think that my results could have a strong impact on my family's finances.

Answer options: five levels from strongly disagree *to* totally agree.

Question C3: Genetic testing willingness. Would you carry out such a genetic test? *Answer options: not likely; unlikely; likely; very likely.*

Additional information disclosure
A genetic test costs between CHF 100 and CHF 400.

Question C4: Genetic testing willingness. Taking these costs into account, would you carry out such a genetic test? *Answer options: not likely; unlikely; likely; very likely.*

Framing for financing of genetic tests.
Framing C Some people say that genetic testing should be paid for by health insurance.

Question C5c: Genetic testing willingness. Would you carry out such a genetic test? *Answer options: not likely; unlikely; likely; very likely.*

Framing D Some people say that genetic testing should be paid for by the individuals themselves.

Question C5d: Genetic testing willingness. Would you carry out such a genetic test? *Answer options: not likely; unlikely; likely; very likely.*

Question C6: Genetic testing willingness. If you were to perform a genetic test, would you share the anonymized test data with your health insurer?
Answer options: not likely; unlikely; likely; very likely.

Question C7: Impact of genetic testing on society. We are now considering the impact of genetic testing on society. For each of the following reasons, indicate your level of agreement. In random order:

1. It will be more difficult for my family members to get an insurance policy.
2. Knowledge related to genetics will lead to fewer illnesses and longer life expectancy.
3. It will be very common to perform a genetic test.

4. Future employees will have to undergo genetic testing before being employed.
5. Insurance companies will request a sequencing of our genome to establish premiums level.
6. In the future we will all have a genetic passport.
7. There will be a separation in our society between the “good" genomes and the “bad" ones.
8. People with disabilities will be less accepted in society.
9. The government will not be able to protect citizens from the negative aspects of genetic testing.
10. The genome of all infants will be sequenced to establish their genetic profile and prevent the development of certain diseases.
11. All pregnant women will undergo genetic testing to determine if the fœtus carries a disease.
Answer options: five levels from strongly disagree *to* totally agree.

Control variables

Question D1: Physical activity. How often do you do gymnastics, fitness or sports?
Answer options: several times a week; once a week; less regularly; never.

Question D2: Lifestyle. How often do you consume these products?
1. Alcohol.
2. Cigarettes, cigars, e-cigarette.
3. Five servings of fruits and vegetables.
Answer options: daily; several times a week; once a week; once every two weeks; once a month; less regularly; never.

Question D3: Health. How do you rate your general health? Is it... *Answer options: very good; good; fairly good; bad; very bad.*

Question D4: Cancer history. Do you have a history of cancer, heart disease or hereditary disease in the immediate family? *Answer options: yes; no.*

Question D5: Risk aversion and planning. How do you evaluate yourself personally?
1. Are you generally interested in planning for the future?
2. Are you generally willing to take risks?
Answer options: ten levels from not interested at all *to* very interested.

Question D6: Health insurance. Which health insurance model do you personally have for compulsory basic insurance?
Answer options: standard model; HMO model; family doctor; CallMed.

Question D7: Health insurance. What is your annual deductible in the compulsory basic insurance? *Answer options: CHF 300; CHF 500; CHF 1 000; CHF 1 500; CHF 2 000; CHF 2 500.*

Question D8: Health insurance. Do you have additional insurance? *Answer options: yes; no.*

Question D9: Health insurance. Do you use an app from your insurer to record the number of steps or sports activities? *Answer options: yes; no.*

Question D10: Political behaviour. For each of the following reasons, indicate your level of agreement.
1. It is the role of the State to plan and guarantee the financing of health care for the entire population through social insurance.
2. It is the role of the State to intervene in the economy to reduce inequalities.
3. It is the role of the State to store and use data.
4. It is the role of the State to regulate the storage and sharing of data.
5. I support the sharing of my social insurance data to create a more efficient social system and with less fraud.
6. I support the sharing of my health data to help research for medical progress.
7. I support the sharing of my bank account data to optimize the fight against tax fraud.
8. I support the sharing of my telephone data (connections and movement profiles) to improve crime and terrorism prevention.
Answer options: five levels from strongly disagree *to* totally agree.

Question D11: Political behaviour. In general, are you interested by politics?
Answer options: not at all interested; slightly interested; fairly interested; very interested.

Question D12: Political behaviour. In politics, we talk about left and right. Where would you rank yourself? *Answer options: eleven levels from* left *to* right.

Question D13: Political behaviour. Do you feel close to a political party and, if so, which one? *Answer options: PS; Les Verts; PDC; PLR; UDC; another / several parties; I do not want to disclose; I do not relate to any.*

Question D14: Political behaviour. You find that the budget of the Confederation, the cantons and the municipalities in Switzerland allocated to health care is ... *Answer options: too high; sufficient; insufficient; too low.*

Question D15: Socio-economic status. What is your marital status? *Answer options: married / registered partnership; other.*

Question D16: Socio-economic status. About the composition of your household :
1. How many people live in your household including yourself?
2. How many children under the age of 18 live in your household?
Numeric answer.

Question D17: Socio-economic status. What is your current professional situation? *Answer options: full-time employee or self-employed (working time over 80%); employed or self-employed part-time (working time less than or equal to 80%); at home / without paid work; retired; other.*

Question D18: Socio-economic status. What is your highest level of education? *Answer options: compulsory school; initial vocational education (vocational maturity, federal certificate of competence, federal vocational education certificate); high school diploma or general culture school (high school diploma, specialized diploma, certificate of general culture) ; higher vocational education and training (federal certificate, federal diploma, higher school diploma); university/EPF, pedagogical or specialized schools (Bachelor, Master, PhD).*

Question D19: Socio-economic status. Taking into account your total household income and wealth, would you rather say that you are ... *Answer options: in a modest situation.; in a slightly below average situation.; in a slightly above average situation.; a well-to-do household..*

Question D20: Socio-economic status. What is your nationality? In case of dual nationality, please indicate your nationality at birth. *Answer options: nationality*

Question D21: Socio-economic status. How many years have you lived in Switzerland? *(Only if did not answer* CH *in question D20.) Answer options: < 1 year; between 1 and 5 years; between 5 and 10 years; more than 10 years.*