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Bridging the gap: Experimental evidence on information provision and health insurance choices

Ana Cecilia Quiroga Gutierrez[1,2] | **Stefan Boes**[1]

[1]Faculty of Health Sciences and Medicine, University of Lucerne, Center for Health, Policy, and Economics, Lucerne, Switzerland

[2]Department of Health, Bern University of Applied Sciences, Institute of Health Economics and Health Policy, Bern, Switzerland

Correspondence
Ana Cecilia Quiroga Gutierrez.
Email: ana.quirogagutierrez@bfh.ch

Abstract

Previous research has shown that individuals do not always make rational decisions when selecting their health insurance, for example, due to the existence of information frictions or mental gaps. We study the effect of specific types of information provision for decision support on health plan choices and test their potential to improve decision quality by implementing a randomized laboratory experiment. We provide personalized and generic aids, differentiate between numerical and visual decision support, and provide one or two optional formats of personalized information. We find that generic aids have no effect on health plan choices while personalized information leads to better choices as measured by several indicators of decision quality. The largest effects were observed for those who "opted in" to visualize personalized information, with immediate and lasting improvements in health insurance decisions. By reducing information frictions, our results suggest that accessible and easy-to-use tools can positively impact health insurance navigation, improve decision-making, and reduce switching costs.

KEYWORDS

consumer choice, health insurance, health plan choice, individual behavior, information for decision support, laboratory

JEL CLASSIFICATION

D81, D83, I13

1 | INTRODUCTION

Adequate health insurance is critical to access necessary health care and reduce the financial burden of severe health events. Nevertheless, previous research has provided ample evidence that individuals do not always make rational decisions that align with their health status, risk preferences, and other circumstances (Bhargava et al., 2015, 2017). Making a suboptimal decision often translates into higher out-of-pocket expenditures, and in extreme cases, it may even lead to foregoing necessary care due to financial reasons or access restrictions (Sandoval et al., 2021).

There are several reasons that have been discussed in the literature that may explain suboptimal health insurance choices. First, health systems and health insurance products are generally complex and often challenging to navigate, making suitable health plan selection difficult. This is particularly true in the face of uncertainty (Kahneman & Tversky, 2012; Thaler, 1978). The issue of selecting an adequate health plan is aggravated by low levels of health insurance literacy (HIL) in the population (Handel et al., 2020; Loewenstein et al., 2013). Both product complexity and low levels of HIL result in information frictions, referring to a lack of information and costs for acquiring it; and mental gaps, that is, psychological distortions that lead to consumers not using relevant information even when available, in part because of a lack of knowledge or understanding (Handel & Schwartzstein, 2018).

In addition, individuals in countries with choice-based health insurance systems, such as the marketplaces in the US, the Netherlands, or Switzerland, face an increasingly large amount of information about health plans in the market, often accompanied by intensive marketing campaigns of insurers that compete for customers (Chernev et al., 2015). The available information might be difficult to process and use effectively, particularly in the presence of low HIL (Park et al., 2022; Parragh & Okrent, 2014). As a result, several initiatives have taken place, mainly in the US, with the aim of providing relevant tools and information platforms to support individuals' health insurance selection (Bartholomae et al., 2016; Bundorf et al., 2019; Politi et al., 2016).

Decision support tools such as the provision of personalized information have been shown to improve decision-making in the context of health insurance (Krishnan S. et al., 2022). However, there is a lack of evidence to date regarding what type or form of information provision would benefit individuals the most by reducing information frictions and issues due to mental gaps. Similarly, there is limited research on how the availability of different decision-support tools might affect whether individuals access them, and if the mode of information provision influences this access decision.

Our paper aims to contribute to this research gap by providing novel evidence on the effect of different types of information, like graphical and numerical information, to support the selection of health plans by implementing a multiperiod randomized laboratory experiment in the context of the Swiss health insurance system. The experiment was designed in a way such that information provision was staggered to examine how the availability of different types of information affects health insurance selection. Participants were randomly assigned to a control group receiving no information for decision support, and four different treatment groups. Information treatments were provided only during the third round of the experiment. All treatment groups received general graphical information for decision support (treatments 1–4), two treatment groups received one optional type of personalized information for health insurance decision support, either graphical (treatment 2) or numerical (treatment 3), in addition to the general information provided to all treatments. The last treatment (4) received both types of optional personalized information in addition to the general information. Inertia and opportunity costs were introduced in the experiment with trivia questions that served as a distraction as well as a means to earn extra points. Participants were compensated based on how many points they accumulated at the end of the experiment.

While general information did not have a significant impact on the studied outcomes, personalized information did. When visualized, personalized information increased the likelihood of switching health insurance, switching with improvement, having the plan with the lowest expected costs (based on the given risk profile), and reducing decision time when switching. Our results indicate that personalized graphical information tended to have a greater and longer-lasting impact compared to numerical information, although the effects were not statistically different between the two types. The results demonstrate that the provision of user-friendly and targeted information for decision support not only has the potential to reduce expected costs for consumers, but can also reduce the time and effort required for decision-making, minimizing opportunity costs.

The remainder of the paper is organized as follows. Section 2 briefly introduces the related literature and further motivates the rationale for conducting the experiment. Section 3 provides information about the institutional context of the Swiss health insurance system. Section 4 states the research questions of the study. Section 5 describes the empirical methods, summarizing the experimental design, the information treatments, the outcome variables, and the collection of background characteristics of study participants. Section 6 presents the results. Section 7 offers concluding remarks.

2 | RELATED LITERATURE AND RATIONALE FOR THE EXPERIMENT

Information frictions can have far-reaching negative consequences in the context of health insurance, given the related health and financial implications of having a suboptimal health plan. These frictions include search and comparison frictions, which refer to the gap between the availability of comparative health plan information and its use by consumers. Previous research has demonstrated that consumers do not always make efficient health plan choices, even when valuable information is available (Bhargava et al., 2017). For example, a randomized field experiment in the US investigated the effect of personalized price information on Medicare drug plan switching (Kling et al., 2012). The results show that individuals who received the personalized information intervention were more likely to switch plans and reduce their costs, indicating a reduction of search and comparison frictions.

Mental gaps also play an essential role. These gaps refer to cases in which information may be available but is not appropriately taken into account in the decision-making process, for example, due to a lack of HIL or "insurance competence" (Handel & Schwartzstein, 2018). Individuals with low levels of HIL, for example, have difficulties understanding health insurance terms, evaluating plan characteristics and costs, are not or insufficiently aware of beneficiary rights, have problems finding relevant information, interpreting benefits, or assessing their own needs and personal risks, they falsely project their future healthcare utilization and calculate cost-sharing (Paez et al., 2014). Research has found that low HIL may lead to inappropriate health insurance choices (Bhargava et al., 2015) and is associated with individuals being more likely to avoid care due to costs (Tipirneni et al., 2018).

In line with these results, a recent study in the US investigated the effect of consequence information provision on health insurance choice in a laboratory experiment, as well as in a hypothetical choice survey experiment (Samek & Sydnor, 2020). The decision aid provided to participants consisted of a "consequence graph" that mapped the spending individuals could expect for each quantile of medical costs they faced. The information provision altered choices considerably and reduced the likelihood of choosing more expensive plans in menus with dominant options. Relatedly, a computer laboratory experiment conducted in Switzerland by Kaufmann et al. (2018) investigated the impact of providing personalized information on deductible choice. The information prompt used in the study consisted of a statement declaring the plan with the lowest expected cost based on the participant's risk profile, as well as expected cost savings. The study found that health insurance choice quality of participants who received the personalized information was better compared to those who did not receive information, and even more so when individuals are distracted.

Similar to mental gaps, choice overload, often referred to as the paradox of choice, or choice paralysis, may affect health plan selection and access to related information. Choice overload is used to describe scenarios in which decision-making is complicated by a large number of alternatives. This can lead to lower satisfaction with one's decision, as well as deferring choice, although evidence is mixed (Chernev et al., 2015; Scheibehenne et al., 2010). For example, a computer laboratory experiment conducted in the Netherlands found that when the number of alternatives of health insurance plans increased, participants would consider less attributes for decision-making, and select plans with higher expected costs (Schram & Sonnemans, 2011). A more recent laboratory experiment confirms these results, demonstrating that with increasing alternatives, decision quality decreases, concluding that low-quality decisions may result from the use of heuristcs (Kairies-Schwarz et al., 2017). While information may facilitate decision-making in these situations, information gathering is not costless (Simon, 1955). This is particularly true nowadays, with multiple sources of information available in online environments. Digitalization has reduced search costs, but information abundance results in higher processing costs, which generates the need to provide information in efficient ways to facilitate decision-making (Wan et al., 2022).

Tools for product comparison and, as previously stated, personalized information provision, can improve decision quality. But the format in which information is presented might affect its efficacy. Some studies have investigated the effect of graphical risk information compared to written or tabular forms (Schirillo & Stone, 2005; Smerecnik et al., 2010), concluding that the use of graphs for risk information provision is a valuable asset as it attracts attention and requires less cognitive effort to be interpreted. Yet, little is known about how the provision of visual or graphical information can affect the decision-making quality in the context-specific area of health insurance.

The present experiment builds on these findings and brings several innovative contributions. First, following Kaufmann et al. (2018), we allow for inertia and limited attention, which have been shown to be pivotal factors in insurance decision-making. Inertia is accounted for by giving study participants the option to switch their insurance at the end of each experimental round, while a distraction was implemented by allowing participants to earn extra points when answering trivia questions during the actual insurance choice task; see also Dhar and Simonson (2003) and Heiss et al. (2021) for related discussions. Compared to the earlier experiments, we allow for different types of health shocks depending on the individual's risk profile: minor events that last only one round and major events that last two rounds. We deem the latter of high relevance in this context because insurance decisions may be triggered by sudden events, rather than a rational assessment of the underlying risk profile.

Second, participants were provided with all the necessary information such that they could calculate their expected healthcare expenditures for the given risk profile. However, the participants had a limited decision time, which introduced an opportunity cost of selecting an appropriate health plan by earning extra points (and money) through correctly answering trivia questions.

Third, and a major distinctive feature of our experiment compared to previous experiments, one type of general information, and two types of personalized information, in a graphical and in a numerical format, were randomly provided to study participants. This allows us to assess the causal impact of specific types of information for decision support on decision-making, and empirically quantify the magnitude of the effect of different types of information provision on the quality of health plan choices. To this end, we also investigate the decision time when selecting health insurance, under the assumptions of bounded rationality and limited attention.

Finally, and fourth, we offer individuals the option to view the personalized information, or not. This design feature is particularly relevant in the context of information frictions and non-zero search costs since the time of viewing the personalized information is subtracted from the total decision time available to study participants. The distinction between graphical and numerical personalized information then matters because individuals may seek an easy-to-understand decision support tool that offers them quickly all the necessary information they need for selecting an appropriate health plan. Additionally, treatments vary in the number of types of information available. This allows us to test for the paradox of choice and its potential effect on accessing information.

As health insurance systems and choice environments grow in complexity, health expenditures rise, and health disparities increase due to gaps in access to care; it is crucial to identify and assess novel decision-support tools aimed at reducing information frictions. Our contribution connects to the literature informing on actionable steps that support individual decision-making. Such steps, when implemented effectively, have the potential to empower individuals to make more informed insurance decisions that benefit their health and financial well-being.

3 | INSTITUTIONAL SETTING

The Swiss health system, and specifically the mandatory health insurance (MHI) system, follows the principles of regulated or "managed" competition to maintain risk solidarity, guarantee accessibility and affordability of care, and ensure efficiency of the health system (Schmid et al., 2018). Managed competition is defined as "a purchasing strategy to obtain maximum value for consumers and employers, using rules for competition derived from microeconomic principles" (Enthoven, 1993). Based on this model, a "sponsor" is given tasks such as establishing equity, selecting participating plans, and managing risk selection. In Switzerland, the Federal Office of Public Health (FOPH) plays the role of this "sponsor" and regulates the competition among health insurers, authorizes premiums, and governs statutory coverage and prices of pharmaceuticals (Camenzind, 2016).

To safeguard universal coverage, cantons (similar to US states) are responsible for enforcing the obliged purchase of health insurance by all residents. At the same time, insurers are obliged to accept any customer who wants to enroll regardless of their risk (open enrollment); this way, customers can choose their insurance company from around 60 competing health insurers in Switzerland depending on which ones compete on their canton or region of residence (Schmid et al., 2018; Schuler, n.d.). Health insurance premiums are community-rated and vary based on age groups (children, young adults, and adults) and up to three premium regions per canton.

Health insurance companies are not allowed to profit from MHI plans, extra income should only be used to accumulate insurance reserves and benefit the customers, and there is a risk adjustment scheme in place to compensate for the unequal distribution of risks across insurers.

Companies offering MHI are obliged to offer the standard health plan, which consists of a minimum annual deductible of CHF 300 plus a co-payment of 10% over all services up to a maximum of 700 CHF per year. This is considered the default option for consumers. Enrollees in the standard health plan can choose freely among general practitioners and outpatient care specialists in their place of work or residence and all listed hospitals on the cantonal list of hospitals defined by the cantonal authority, and in some cases, services can also be covered outside the canton of work or residence (De Pietro et al., 2015; Schmid et al., 2018; Tikkanen et al., 2020). In addition, other health insurance options are available for consumers, which allow for lower premiums. These alternatives vary according to two parameters: higher voluntary deductibles and the type of health insurance model. Voluntary deductibles for adults include the options CHF 500, 1000, 1500, 2000, or 2500 (FOPH, n.d.).

Individuals have the option of changing the insurer, the deductible, and the type of health plan every year. Updated MHI premiums are published annually at the end of September after being approved by the FOPH. By the end of October, insurance companies inform insurees of their new premiums. Then, insured persons can notify their insurer about their policy termination no later than the end of November to switch plans for the following year. Termination of a health insurance plan does not take place until the new insurer notifies the old one about the consumer's further coverage to prevent individuals from avoiding the requirement of having MHI (Schmid et al., 2018).

Recent research in Switzerland has found that income is negatively associated with the demand for health insurance coverage, with lower-income individuals being more likely to select low deductibles and being over-insured, conditional on good health status (Zou & Biener, 2022). This results in an average loss of 347 CHF a year at the individual level, and the loss due to over-insurance is even larger for those who are healthy and have a low income with 1028 CHF per year.

4 | RESEARCH QUESTIONS

Multiple sources of information can be found online and offline to navigate the Swiss health insurance system. Nevertheless, various factors, such as information frictions, including mental gaps, and choice overload, hinder optimal health insurance selection. Based on the previously discussed literature and context of the Swiss health system, we investigate whether information provision for decision support can help individuals make better choices when it comes to selecting a health plan.

To analyze whether the number of available information sources affects the access to information for decision support in the context of health insurance, our first research question focuses on whether participants with one or multiple options of information types are likely to access it. We hypothesize that more information options decrease the likelihood of accessing information sources:

> Research Question 1. Does the number of available information options affect the likelihood of accessing personalized information for health insurance decision support?

There are several reasons why individuals may not switch their health plan, sticking to their previous suboptimal choice. Some of these reasons include inertia, status quo bias, and switching costs. Information provision may serve as a prompt that could help disrupt inertia, or lessen switching costs by reducing information frictions. For example, if personalized information takes less time to be understood and interpreted, then the time necessary for decision-making might be shortened, minimizing switching costs in terms of time and effort. Our second research question investigates how information provision affects switching behavior. We hypothesize that providing personalized information will increase the likelihood of switching health plans.

> Research Question 2. How does information provision, and access to different types of decision support, affect switching behavior?

While information provision has been shown to improve decision-making, there is limited evidence on how this information should be presented in order to be easily understood and maximize its impact. Our last research question focuses on which of the graphical and numerical personalized information has a greater impact on choice quality and decision time. Choice quality was assessed based on expected costs, and we hypothesize that providing information that can be more easily processed and used by individuals would lead to selecting a health plan with lower expected costs. Decision time was quantified by the number of seconds spent switching health insurance. We hypothesize that successful tools for decision-support and information provision would reduce opportunity costs associated with switching health plans, and thus reduce the time spent switching plans.

Research Question 3. What kind of information provision do individuals benefit the most from when choosing health insurance?

5 | METHODS

5.1 | Experimental design

The design of the experimental tool was based on a previous experiment to mimic aspects of the Swiss health insurance market (Kaufmann et al., 2018). The game was programmed using oTree, an open-source, web-based platform for experiments (Chen et al., 2016), and played at laboratories of two Swiss universities in the German-speaking region from October 2021 to April 2022. Participants were recruited through the Research Pool of the University of Lucerne and the Research Pool of the Decision Science Laboratory of the Swiss Federal Institute of Technology in Zurich.

Screenshots of the experiment can be found in Appendix 1. After being instructed to start, participants were asked to read on-screen instructions and answer review questions to ensure they understood what the experiment was about. The experiment consisted of 12 consecutive rounds during which participants could gain and lose points that would be reflected in their "account". For the purpose of this paper, only data corresponding to the first seven rounds was used.[1] For the first round, each participant had a starting balance of 500 points and was assigned to a "health insurance" with a deductible of 300 points and a premium of 4900 points per round. On each round, participants could earn extra points by receiving a fixed income of 5200 points, correctly answering trivia questions (10 points per correct answer); they could also realize if any "health events" took place, and change their health insurance plan. Participants would lose points by paying their health insurance plan's premium and deductible, depending on the cost of the health events that took place during the current and the previous round. All participants had the same risk profile and income throughout rounds 1–7. To ensure that participants understood the probability of events taking place and the related costs, they answered comprehension questions during the instructions section, and could not continue until the correct answer was provided. Instructions and screen examples are available in the supplementary material for further reference.

At the end of each round, two types of "health events" could occur simultaneously: a minor health event (A or B), and a major health event. Minor health events affected the costs of the current round only. Minor event A had a cost of 250 points, while minor event B had a cost of 1300 points. Major health events were more expensive, incurring costs of 3000 points, and affected two consecutive rounds. A major health event could take place even if there was a major health event in the previous round. Minor and major health events were independent of each other. The likelihood of health events taking place was based on the participant's risk profile, which was displayed in each round. The risk profile was the same for all participants, and it did not change during rounds 1–7.

After realizing the health events that took place during the round, participants had the option of changing their health insurance for the next round. The available plans were chosen to resemble the Swiss health insurance market, with available deductible levels at 300, 500, 1000, 1500, 2000, and 2500 points. Premium prices (in points) were based on average premiums in Switzerland in 2021. The time that participants spent switching their health insurance plan was subtracted from the time available to answer trivia questions during the status overview screen in the following round.

After the experiment concluded, participants were compensated by converting the final balance of their fictional experiment "account" into Swiss Francs at a fixed rate. Additionally, participants were paid a fixed amount of 10 CHF for participating in the experiment. In case of finalizing the experiment with a negative account balance ($n = 8$), participants were paid the 10 CHF participation fee.

5.2 | Control group and information treatments

Participants in the control group went through the 12 rounds of the experiment without receiving any type of information for decision support. In each round, participants had 2 minutes to answer trivia questions and earn extra points. At the end of the round, participants had 75 s to make an active choice regarding whether they wanted to see the available health insurance plans.

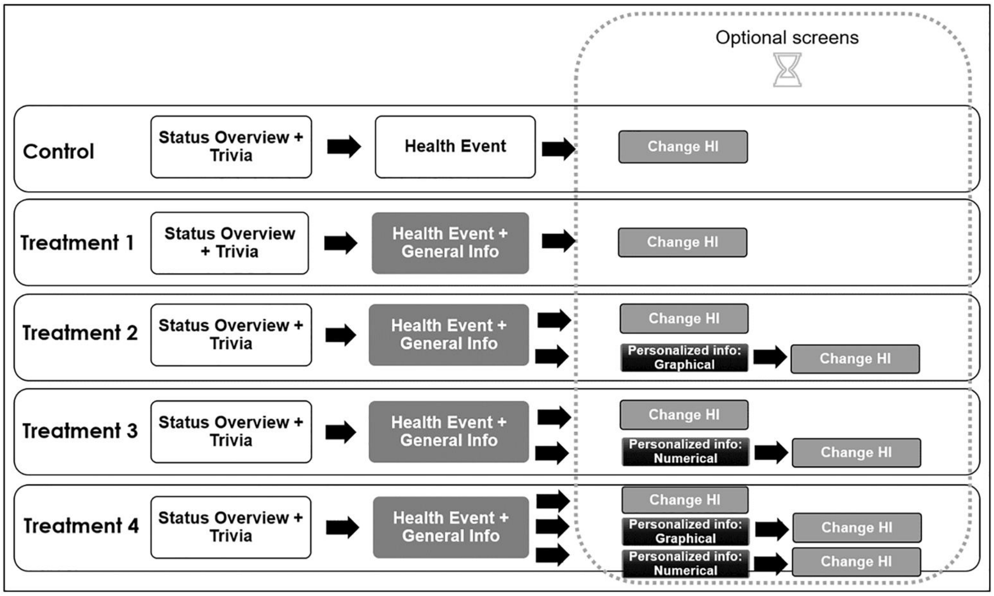


FIGURE 1 Screen flow for control and treatment groups on round 3. Participants on all treatments received general information during the health event screen of round 3. The time that participants spent on optional screens like when changing health insurance or visualizing personalized information, was subtracted from the time available for the status overview and trivia screen of the next round.

There were four different treatments that provided different types of information for decision support to participants in round 3 (see also Figure 1 for an overview):

Treatment 1 consisted of the provision of general information for decision support at the end of round 3, after participants realized the events taking place in the round. The general information consisted of a graph showing the expected costs for each plan depending on expected health expenses.

Treatment 2 consisted of the provision of the same general information as treatment 1. Additionally, participants were asked if they wished to receive personalized information based on their risk profile and expected health costs. Those who opted to visualize the additional personalized information were provided with a statement of which plan had the lowest expected costs based on the participant's risk profile. The visualization was based on the same graph presented as general information, with the difference of a vertical line signaling the expected costs given the participant's risk profile. The time spent visualizing the personalized information was subtracted from the time available to answer trivia questions in the next round.

Treatment 3 was similar to treatment 2 in that participants were shown the unqualified general information, and given the option to receive personalized information. While treatment 2 provided graphical information, the type of personalized information provided to treatment group 3 consisted of numerical information regarding what plan had the lowest expected costs based on their risk profile, with a table showing all plans with lower expected costs, along with expected savings compared to the current plan. Like in treatment 2, the time participants spent visualizing the personalized information was subtracted from the time available to answer trivia questions.

Treatment 4 was different from treatments 2 and 3 in that participants had the option of choosing between the two types of personalized information, graphical or numerical.

5.3 | Outcome variables

5.3.1 | Visualizing personalized information

Visualizing personalized information is a binary variable, taking the value of one if the participant chose to visualize some type of personalized information in treatments 2, 3, or 4. This variable is zero for those participants on these treatments who chose not to visualize personalized information or did not make an active choice during the allocated time regarding personalized information visualization.

5.3.2 | Switching

At the end of each round and after realizing the health events and costs that took place, participants had the opportunity to switch their health insurance, that is, their level of deductible, for the next round. The variable *switching* is a binary variable taking the value of one for participants who changed their current health insurance deductible in the next round.

5.3.3 | Switching with improvement

The variable *switching with improvement* is a binary variable that equals one for participants switching to a deductible with lower expected costs than their current plan, based on their risk profile.

5.3.4 | Distance to plan with lowest expected cost

All participants were given the same risk profile that described the probabilities of the different health events and the associated costs. Based on this risk profile, the expected health costs can be calculated. *Distance to plan with lowest expected cost* is a continuous variable that equals the expected cost of the current health insurance plan minus the expected cost of the health plan with the lowest expected cost. The value of this variable is bounded at zero for a participant with a deductible that yields the lowest expected expenditures and is positive otherwise. For all participants, the distance to the plan with the lowest expected expenditures is 774 points in round 1 since participants are assigned the standard plan at the beginning of the experiment, which has the highest expected cost.

5.3.5 | Having plan with lowest expected cost

Having plan with lowest expected cost is a binary variable, taking the value of one for participants having the deductible with the lowest expected cost based on their risk profile, and zero otherwise. This would correspond to having a distance to the plan with the lowest expected cost of zero.

5.3.6 | Time spent on plan selection

Time spent on plan selection is a variable that records the seconds spent by participants selecting a health plan, storing the amount of time spent on the page presenting the available plans. This variable has a missing value for participants who did not select to change their deductible while visualizing the "Health Event" page and therefore is conditional on viewing the plan selection page.

5.4 | Background characteristics

After completing the 12 rounds of the experiment, all participants completed a survey, which included questions on demographic and socio-economic background, health status, risk preferences, health insurance objective knowledge, HIL, and decisional conflict.

Risk preference was elicited with a self-reported question on willingness to take risks; participants could respond on a scale from zero (not at all willing to take risks) to ten (very willing to take risks). Health insurance objective knowledge was assessed with 10 questions regarding the Swiss health insurance system. Health insurance literacy (HIL) was measured using the HIL Measure for Switzerland (HILM-CH) (Bardy & Boes, 2022). Decision conflict was evaluated using the SURE scale, a 4-item test for decisional conflict (Garvelink et al., 2019; Légaré et al., 2010).

6 | RESULTS

6.1 | Participant characteristics

A total of 433 individuals participated in the experiment, with participants being evenly distributed between the control and treatment groups in both laboratories. Table 1 shows the sample and group characteristics. Given the participant pools of mainly university students in the two labs where we conducted the experiment, the average age of the participants was relatively low at 23.4 years old, with 54.5% of the sample being female, and 44.6% being Swiss nationals. Notably, there were some differences in the proportion of female participants (0.705 vs. 0.523, $p = 0.0070$), and age (24.96 vs. 23.20, $p = 0.0006$) between the two laboratories,[2] pointing to heterogeneity within the participant sample. Despite these differences, Table 2 shows that control and treatment groups were balanced on subject observables such as gender, age, and university education.

About 41% of the participants reported not knowing what the deductible level for their actual health insurance was, while 23.56% reported having a deductible of 300 CHF (lowest deductible), 10.62% 2500 CHF (highest deductible), and the rest were distributed among other deductible levels. 33% of the participants reported never having switched their health plan, 24.25% doing it last year, 11.55% 2 years ago, 18.94% more than 2 years ago, and 12.24% did not know when they last changed their health insurance. Regarding income, 78.52% of the participants reported earning less than 12,000 CHF a year, 12.70% reported earning 12,000–24,000, and the rest reported earning more than 24,000 CHF a year. These and further descriptive statistics can be found in appendix 2.

TABLE 1 Sample background characteristics.

Variable	Description	Sample	Control	T1	T2	T3	T4
Female	= 1 if participant is female, = 0 if participant is male	0.545	0.552	0.558	0.518	0.558	0.539
		(0.499)	(0.500)	(0.500)	(0.503)	(0.500)	(0.501)
Age	Participant's age	23.411	23.414	23.163	22.894	23.698	23.865
		(3.667)	(3.439)	(2.894)	(3.292)	(4.229)	(4.259)
Swiss	= 1 if participant is Swiss, = 0 otherwise	0.446	0.414	0.442	0.471	0.512	0.393
		(0.498)	(0.495)	(0.500)	(0.502)	(0.503)	(0.491)
University	= 1 if participant has a university or higher education degree, = 0 otherwise	0.841	0.897	0.849	0.800	0.779	0.876
		(0.366)	(0.306)	(0.360)	(0.402)	(0.417)	0.3310
Health Sciences	= 1 if participant studies health sciences or related, = 0 otherwise	0.143	0.126	0.140	0.177	0.116	0.157
		(0.351)	(0.334)	(0.349)	(0.384)	(0.322)	(0.366)
Health status	Likert scale from 1 to 5, with 1 being very poor and 5 being very good	4.305	4.138	4.454	4.235	4.361	4.337
		(0.760)	(0.878)	(0.663)	(0.718)	(0.766)	(0.738)
HI objective knowledge	Total score of health insurance objective knowledge quiz (0–10)	3.704	3.632	3.872	3.318	3.640	4.045
		(1.832)	(1.948)	(1.748)	(1.929)	(1.666)	(1.815)
HILM confidence scales	Average of arithmetic mean of HILM confidence scales	2.538	2.509	2.510	2.537	2.568	2.567
		(0.594)	(0.608)	(0.601)	(0.585)	(0.547)	(0.633)
HILM behavior scales	Average of arithmetic mean of HILM behavior scales	2.881	2.898	2.871	2.821	2.928	2.887
		(0.554)	(0.556)	(0.546)	(0.523)	(0.526)	(0.619)
SURE scale	Cumulative score for SURE scale	2.286	2.207	2.267	2.259	2.314	2.382
		(1.334)	(1.365)	(1.340)	(1.320)	(1.313)	(1.353)
Number of observations (N)		433	87	86	85	86	89

Note: The table shows mean values of the main background characteristics of individuals included in the sample. The sample is split randomly into a control group and four treatment groups. T1 received general information only, T2 received the option to view personalized graphical information, T3 received the option to view personalized numerical information, and T4 received the option to view either personalized graphical or numerical information. Standard deviations are in parentheses.

TABLE 2 Balance table.

Variable	Between groups difference (*p*-value)	Bonferroni multiple comparison test									
		T1 − C	T2 − C	T2 − T1	T3 − C	T3 − T1	T3 − T2	T4 − C	T4 − T1	T4 − T2	T4 − T3
Female	0.9825	0.006	−0.034	−0.040	0.006	0.000	−0.040	−0.012	−0.019	0.022	−0.019
		1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Age	0.4108	−0.251	−0.520	−0.269	0.284	0.535	−0.804	0.451	0.702	0.971	0.167
		1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.815	1.000
Swiss	0.5474	0.028	0.057	0.029	0.098	0.070	0.041	−0.021	−0.049	−0.077	−0.118
		1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Uni	0.1717	−0.048	−0.097	−0.049	−0.117	−0.070	0.021	−0.020	0.028	0.076	0.097
		1.000	0.839	1.000	0.351	1.000	1.000	1.000	1.000	1.000	0.788

Note: The table shows the results of mean comparison tests (ANOVAs) with Bonferroni correction for multiple comparisons. For a description of the treatment groups, see Table 1; C: control group.

Participants spent an average of 17.19 (SD = 1.41) minutes on rounds 1–7 of the experiment. At this point, they accumulated an average of 3324.83 points (SD = 2670.915).

6.2 | Visualization of personalized information

Personalized information was made available during round 3 for treatment groups 2, 3, and 4, in the same round during which participants visualized general decision support information (all treatment groups). While 42% of the participants allocated to treatments 2 and 3 viewed the personalized information during round 3, only 31% of the participants in treatment 4 did so.

To investigate these compliance rates in more detail and to appropriately answer question 1 on the likelihood of participants "opting in" to visualize personalized information for decision support, a first-stage analysis was performed using data from the third round exclusively (Table 3). Using linear probability models, we regressed the binary variable for visualizing personalized information on indicators for the treatment groups 2–4 and the set of background characteristics, using the control group as a reference, which by design could not view the personalized information and also had no other means of decision support. The estimated coefficients for the treatment groups can be interpreted causally and represent compliance rates of the treated to follow our incentive of accessing personalized information for insurance decision support. The results indicate no significant difference in the compliance rates for visualizing personalized information between the treatments receiving one type of optional personalized information (treatments 2 and 3). On the other hand, participants who were offered two types of optional personalized information at the same time (treatment 4) were less likely to view any of the two types by approximately 7% points compared to participants who only had one type of personalized information offered to them. It should be noted, however, that this difference is statistically significant only at the 10%-level when omitting control variables (*p*-value 0.088) and becomes insignificant when control variables are included (*p*-value 0.18).

6.3 | Switching behavior

The proportion of participants viewing the available options of health insurance plans varied between 30.3% (round 5) and 56.4% (round 1), with no significant differences between treatment groups. On average, 81.0% of participants who visualized the available plans switched to a different plan in the following round (rounds 1–6); further descriptive statistics can be found in appendix 2, including the proportion of participants switching and switching with improvement.

To answer the question of how the provision of different types of information for decision support affected the participants' switching behavior, we used two outcomes: switching, and switching with improvement. Ordinary least

TABLE 3 First stage analysis: compliance rates for visualization of personalized information.

	(1) Personalized info	(2) Personalized info	(3) Numerical personal info	(4) Numerical personal info	(5) Graphical personal info	(6) Graphical personal info
Treatment indicators						
T2	0.405***	0.409***			0.415***	0.422***
	(0.0584)	(0.0588)			(0.0574)	(0.0576)
T3	0.403***	0.406***	0.412***	0.414***		
	(0.0563)	(0.0567)	(0.0565)	(0.0565)		
T4	0.327***	0.320***	0.193***	0.189***	0.134**	0.127**
	(0.0537)	(0.0534)	(0.0448)	(0.0447)	(0.0423)	(0.0432)
Background characteristics						
Female	−0.114*	−0.113*	−0.108*	−0.104*	−0.0416	−0.0420
	(0.0526)	(0.0528)	(0.0520)	(0.0521)	(0.0529)	(0.0530)
Age	−0.00722	−0.00910	−0.00767	−0.00906	−0.00181	−0.00345
	(0.00562)	(0.00587)	(0.00562)	(0.00598)	(0.00555)	(0.00553)
Uni	−0.0435	−0.0491	−0.0114	−0.00884	−0.0378	−0.0454
	(0.0744)	(0.0741)	(0.0797)	(0.0794)	(0.0782)	(0.0774)
Swiss	−0.0209	−0.0305	−0.0260	−0.0314	0.00370	−0.0114
	(0.0554)	(0.0559)	(0.0528)	(0.0536)	(0.0550)	(0.0563)
SURE scale	−0.0141	−0.0134	−0.0294	−0.0192	0.0105	0.00423
	(0.0189)	(0.0209)	(0.0186)	(0.0220)	(0.0176)	(0.0195)
General risk	0.00337	0.00373	0.0104	0.0122	−0.00277	−0.00335
	(0.0118)	(0.0119)	(0.0123)	(0.0123)	(0.0113)	(0.0113)
Minor event	0.00852	0.00861	−0.0262	−0.0241	0.0344	0.0320
	(0.0301)	(0.0302)	(0.0289)	(0.0290)	(0.0290)	(0.0293)
Major event (current round)	0.0848	0.0758	0.0961	0.0997	0.0267	0.0162
	(0.0775)	(0.0778)	(0.0850)	(0.0851)	(0.0722)	(0.0732)
Major event (previous round)	0.0142	0.0142	0.00535	0.00425	0.00422	0.00769
	(0.0795)	(0.0803)	(0.0784)	(0.0786)	(0.0850)	(0.0853)
Objective HI knowledge		0.0190		0.00204		0.0216
		(0.0139)		(0.0138)		(0.0135)
HILM-CH		−0.00121		−0.00214		0.0000754
		(0.00155)		(0.00154)		(0.00143)
Constant	0.245	0.284	0.214	0.328	0.0867	0.0633
	(0.199)	(0.222)	(0.195)	(0.216)	(0.192)	(0.211)
F-statistic	42.40	42.39	33.18	33.04	30.31	30.85
N	347	347	262	262	261	261

Note: The table shows the estimated coefficients of linear probability models for the likelihood of visualizing the personalized info treatments in round 3 for the treatment groups that had the option to view personalized information compared to the control group. For a more detailed description of the treatment groups, see Table 1. Columns 1 and 2 are based on the control group and treatment groups T2 – T4. Columns 3 and 4 exclude treatment group T2 as participants in T2 had no access to numerical personalized information; columns 5 and 6 exclude treatment group T3 as participants in T3 had no access to graphical personalized information. HILM-CH: Health Insurance Literacy Measure for Switzerland. Pooled difference between the average of treatments T2 and T3 versus treatment T4 (T2 + T3)/2 – T4: 0.106 ($p = 0.088$) in a model without any controls, and 0.088 ($p = 0.184$) in the model with controls as shown in column 2. Robust standard errors in parentheses.

Significance levels: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

TABLE 4 Effect of information on switching HI plan (round 3).

	OLS (1)	IV (2)	IV (3)	OLS (4)	IV (5)	IV (6)
	Switching			**Switching with improvement**		
General information	0.0481			0.0720		
	(0.0725)			(0.0662)		
Personalized information (pooled)		0.229			0.390**	
		(0.146)			(0.128)	
Personalized numerical info			0.213			0.375*
			(0.170)			(0.151)
Personalized graph info			0.245			0.405**
			(0.168)			(0.147)
N	173	347	347	173	347	347

Note: The table shows the estimated coefficients of linear probability models estimated by OLS (columns 1 and 4) and IV (all other columns) for the likelihood of switching the health plan at the end of the round with the information treatment (round 3), and the likelihood of switching with improvement (i.e., to a health plan with lower expected costs). First stage estimates for IV regressions are those presented in Table 3. All models control for gender, age, education, nationality, canton of residence, decisional conflict, risk attitude (see Table 1), and the health events taking place in the experiment. Robust standard errors in parentheses.

Significance levels: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

squares regressions were performed to compare the effect of general information (treatment 1) against no information (control) since the treatment groups were randomized and the visualization of general information was exogenous for T1. Linear instrumental variable (IV) regressions were performed to analyze the effect of viewing personalized information given that visualization of this information was optional, and therefore endogenous.[3] However, the allocation to treatment groups 2–4 can be used as an IV for the actual visualization of personalized information. For this analysis, data from the third round of the experiment was used, as this is when the decision support information was provided to participants.

While no difference in switching rates was found between the control and those in treatment group 1, personalized information increased the likelihood of switching the deductible at the end of round 3 (Table 4). When looking at switching with improvement, general information has no significant effect, while personalized information increases the likelihood of switching to a lower-cost health plan.

6.4 | Health insurance choice quality and decision time

Research question 3 investigates what kind of information individuals benefit the most from when choosing health insurance. To answer this question, three outcomes were used: distance from the plan with the lowest expected cost, having the plan with the lowest expected cost, and time spent on plan selection. Similar to the analysis for switching and switching with improvement, Ordinary least squares regressions were performed to compare the effect of general information (treatment 1) against no information, and IV regressions were used to estimate the effect of viewing personalized information (treatments 2–4), using treatment allocation as an IV, given that access to personalized information was optional. Data from rounds four to seven were used to assess the effect of general and personalized information (provided in round 3) on health insurance choice quality.

General information provided to participants had a small and statistically insignificant effect on the average distance to the plan with the lowest expected cost on rounds 4–7, while personalized information had a greater and significant effect (Table 5, Figure 2). When analyzing the impact of numerical and graphical personalized information, both have a large and significant effect on choice quality (1% level). As shown in Figure 2c, even though the difference is not statistically significant, the personalized graphical information seems to have a slightly larger and longer-lasting effect on the distance to the plan with the lowest expected cost compared to the numerical information. Individuals that reported being more confident in their choices, having a higher decisional conflict scale (SURE) score, had a slightly

TABLE 5 Effect of information on distance to plan with lowest expected cost (rounds 4–7).

	OLS (1)	IV (2)	IV (3)	OLS (4)	IV (5)	IV (6)
	Distance to plan with lowest expected cost			Has plan with lowest expected cost		
General information	−17.10			0.0242		
	(26.64)			(0.0445)		
Personalized information (pooled)		−224.3***			0.275**	
		(60.46)			(0.0956)	
Personalized numerical info			−194.1**			0.220
			(71.82)			(0.114)
Personalized graph info			−253.4***			0.329**
			(73.45)			(0.118)
Balance/100	−11.7***	−9.13***	−9.07***	0.0139***	0.0103***	0.0102***
	(0.580)	(0.581)	(0.592)	(0.00101)	(0.000989)	(0.000997)
SURE scale	−20.02	−22.45*	−22.07*	0.0210	0.0301*	0.0294*
	(10.78)	(8.758)	(8.831)	(0.0166)	(0.0140)	(0.0141)
Risk attitude	−10.61	−11.03	−11.38*	0.0189	0.0166	0.0172
	(6.457)	(5.696)	(5.774)	(0.0107)	(0.00909)	(0.00919)
N	173	347	347	173	347	347

Note: The table shows the estimated coefficients of linear regressions estimated by OLS (columns 1 and 4) and IV (all other columns) for the distance to the plan with the lowest expected cost and for having the plan with the lowest expected cost as an average over rounds 4–7 (following the provision of information treatments); see also Figures 2 and 3. First stage estimates for IV regressions are those presented in Table 3. All models control for gender, age, education, nationality, canton of residence, decisional conflict (SURE scale), risk attitude, and the health events taking place in the experiment. Clustered standard errors at the participant level in parentheses.

Significance levels: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

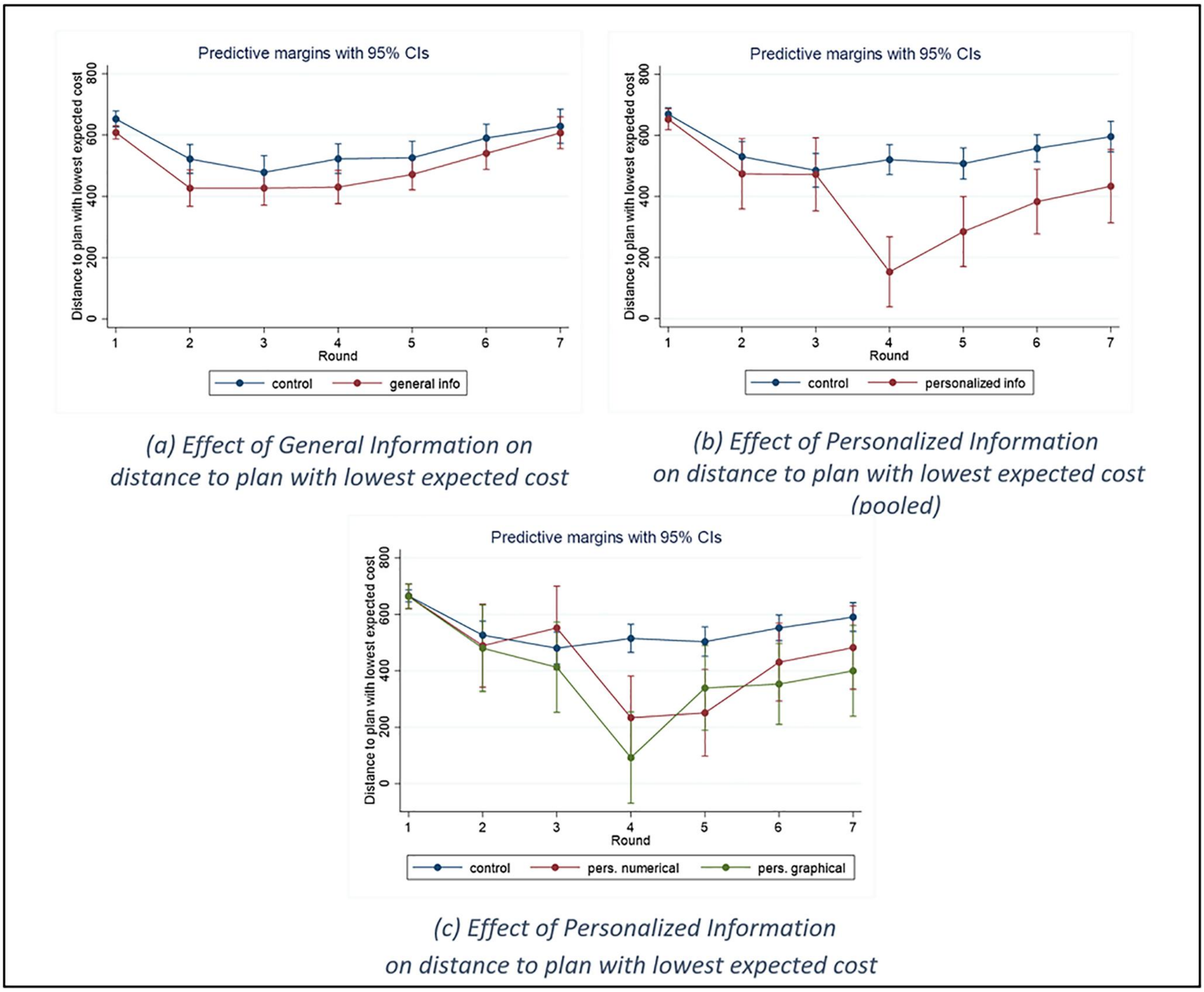
shorter distance to the plan with the lowest expected cost. Similarly, participants who accumulated more wealth (had a higher balance in their account) had a shorter distance to the plan with the lowest expected cost; this association is highly significant at the 0.01% level.

The effect of information on whether participants have the plan with the lowest expected cost given their risk profile is congruent to that of the distance measure (see also Figure 3). While general information does not seem to have a significant effect, receiving personalized information does increase the likelihood of selecting the plan with the lowest expected cost. Most of the impact of personalized information is driven by the graphical information, which increases the likelihood of having the plan with the lowest expected cost by approximately 32.9%-points. This effect is significant at the 1% level. Accumulated wealth was also highly significant for this outcome.

Finally, we measure the effect of information on time spent selecting health insurance for round 4, right after the information was provided at the end of round 3. Table 6 shows the effect of the different types of information on selection time for (a) all the participants who switched insurance for round 4, and (b) those who switched with improvement. The times spent visualizing available health plans in the previous rounds were included as controls. Just as for the previously mentioned outcomes, personalized information significantly reduces the time spent choosing health insurance for the following round, and most of this effect is driven by personalized graphical information.

7 | DISCUSSION AND CONCLUDING REMARKS

Our results corroborate previous findings on how the provision of information and tools for decision support in the context of health insurance can help individuals make better health plan choices. By reducing prevalent information frictions, for example, due to search and comparison costs, choice overload, and mental gaps related to a lack of suitable



(a) Effect of General Information on distance to plan with lowest expected cost

(b) Effect of Personalized Information on distance to plan with lowest expected cost (pooled)

(c) Effect of Personalized Information on distance to plan with lowest expected cost

FIGURE 2 Effect of information on distance to plan with lowest expected cost.

(health) insurance literacy, targeted information provision can support individuals in selecting a health plan that better fits their risk profile and reduces overall out-of-pocket expenditures. Our results show that both graphical and numerical summaries of information for decision support can significantly improve choice quality.

This study's results also highlight that information provision per se is not enough to support individual decision-making. First, participants in the control group were intrinsically provided with all the necessary information to calculate their expected out-of-pocket expenditures through a given risk profile and explicit cost of potential health events for each round. Second, general information provided to treatment group 1 had a negligible effect on all the outcomes considered in the study. The ineffectiveness of such generic information in complex choice settings like health insurance is likely due to the mentioned information frictions, and it is aggravated by issues of inertia and limited attention (the latter as incentivized in our experiment). Instead, personalized information significantly improved decision-making, increasing the likelihood of switching to a health plan with lower out-of-pocket expenditures, and reducing decision times. These results imply that personalized information presented in a suitable format bears the highest potential in simplifying decision-making, and related tools seem particularly promising in reducing information frictions. While the difference between the treatment effects of personalized graphical and personalized numerical information turns out not statistically significant, we found a systematic pattern in our results. Given limitations such as sample size, low rates of treatment compliance for personalized information, and the increased variance associated with an IV analysis, further research is needed to study the effects of personalized information treatments presented in different formats to determine whether graphical information indeed has a stronger and longer-lasting

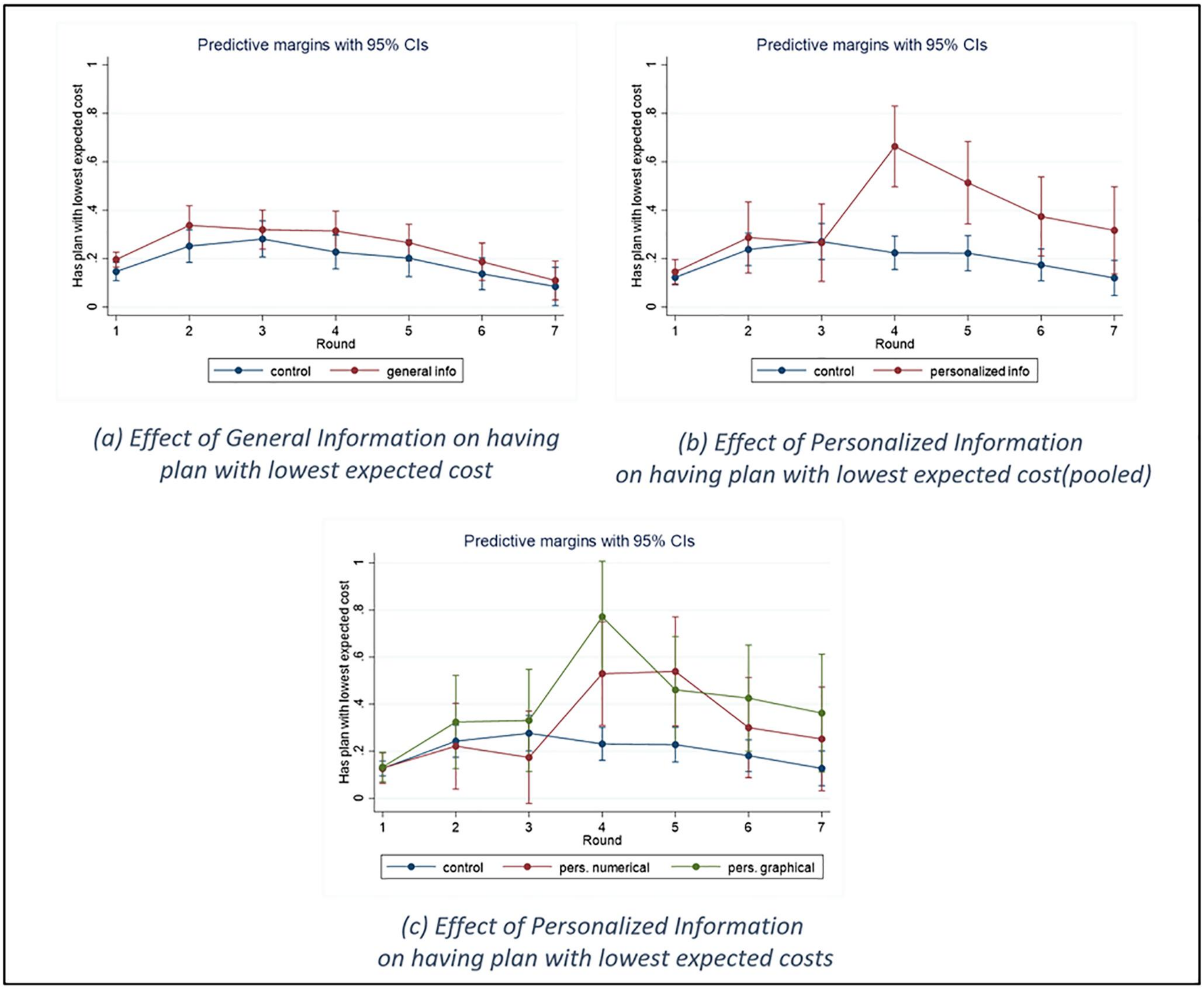


FIGURE 3 Effect of information on having plan with lowest expected cost.

impact on individuals' decision-making compared to other formats of information provision. Heterogeneity in treatment effects is another topic that deserves further scrutiny and is explored in a separate paper.

While these are promising results, other aspects should be considered for decision-support tools to have the desired impact. Access to personalized information has the potential of improving choice quality, but information provision in the real world is not as straightforward as in a laboratory setting (Loewenstein & Bhargava, 2016). Furthermore, the information overload may represent an obstacle for some individuals and potentially reduce choice quality. In line with previous research regarding choice overload, our results indicate that participants are less likely to access personalized information for decision support when multiple information sources are available. However, it is important to note that this effect was only significant at the 10% level without control variables and became statistically insignificant upon the inclusion of covariates. Therefore, these results need to be interpreted carefully. For information to positively impact those who need it the most, accessible and easy-to-use tools are preferred to avoid information overload as well as decision fatigue. Similarly, tools should be targeted at groups that are most in need of them. This is central to ensuring that inequalities in the population in terms of costs and access to care are not exacerbated.

Thus, given the complexity of health insurance, policymakers should strive for simplicity and transparency in designing the health insurance system (Bhargava & Loewenstein, 2015). While decision-support tools can aid individuals in making adequate health plan choices, other choice architecture elements should be considered. Examples include the use of defaults and limiting the number of available choice alternatives (Johnson et al., 2012).

TABLE 6 Effect of information on time spent changing health insurance.

	(a) Effect of information on time spent changing HI for all those who switched			(b) Effect of information on time spent changing HI for those who switched with improvement		
	OLS (1)	IV (2)	IV (3)	OLS (4)	IV (5)	IV (6)
	Time spent changing HI			Time spent changing HI		
General information	−1.128			−7.218		
	(4.858)			(5.400)		
Personalized information (pooled)		−12.69*			−11.95*	
		(5.016)			(5.505)	
Personalized numerical info			−10.25			−11.22
			(5.967)			(5.991)
Personalized graph info			−14.99**			−12.57*
			(5.247)			(5.872)
N	84	167	167	43	116	116

Note: The table shows the estimated coefficients of linear regressions estimated by OLS (columns 1 and 4) and IV (all other columns) for the time spent changing health insurance for those who switched (a) and those who switched with improvement (b) for round 4 (after information provision). First stage estimates for IV regressions are those presented in Table 3. All models control for gender, age, education, nationality, canton of residence, decisional conflict, risk attitude, the health events taking place in the experiment, balance, and time spent visualizing health insurance plans in previous rounds. Robust standard errors in parentheses.

Significance levels: $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

This paper does not come without limitations. First, even though steps were taken to mimic real-world scenarios by introducing distraction elements, restricting the time for decision-making, introducing a trade-off between receiving information and earning extra points, and the use of uncertainty with a risk profile and health events, the laboratory experiment is still simple compared to actual health insurance decisions. For example, the experimental tool offered participants 6 options for health plans that varied only in the deductible level and premiums, while real-life choices vary in additional ways, from prices offered by different insurers to diverse insurance models. Second, as it is usually discussed in the case of laboratory experiments, this study elicits hypothetical choices that might not reflect those made in real-life settings, although there is evidence that such choices translate into real decisions (Kesternich et al., 2013).

As is common with experimental studies, the sample is restricted to students registered in the universities' research pools, which raises considerations regarding external validity. This population is characterized by having higher education and cognitive abilities compared to the general population. At the same time, this population is younger and often has better health status, is more likely to be risk-loving, has lower incomes, and has less experience with health insurance compared to older adults. While such characteristics must be considered when generalizing this study's results to a broader population (Sears, 1986), it is worth noting that our findings empirically support established theories (Krishnan S. et al., 2022; Lucas, 2003) and align with previous evidence (Kaufmann et al., 2018; Krishnan S. et al., 2022; Samek & Sydnor, 2020).

Additionally, personalized information provided to participants was based on a fixed risk profile that allowed them to calculate expected costs, while in real life, even if individuals might have knowledge of their health status, they face uncertainty regarding costs. Finally, while the interventions tested here address some of the issues and biases that may lead to suboptimal decisions, the used treatments might ignore other factors that could affect decisions, for example, endowment effects or personal preferences.

Despite these limitations, our findings inform recent initiatives for consumer empowerment in the context of regulated-competition markets for health insurance, such as the Swiss and Dutch systems, or other countries with choice-based systems like the US and Germany. Similarly, the results on the impact of different types of information provision might be relevant in settings where individuals need to navigate complex systems beyond health and health insurance, such as social insurance (Ståhl et al., 2021), retirement planning (Balzli, 2021;

Brown & Graf, 2013), or the purchasing of products with high financial impacts such as durable goods (Hefti et al., 2021).

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

ORCID

Ana Cecilia Quiroga Gutierrez https://orcid.org/0000-0003-1649-6680

Stefan Boes https://orcid.org/0000-0001-5478-9105

ENDNOTES

[1] Participants' risk profile changed in round 8 to simulate an "aging" effect. Additionally, information treatments were provided again during round 8. These elements added two additional layers to the decision problem that participants faced during the experiment in later rounds (8–12). For the purpose of this paper, rounds 8–12 were therefore excluded from the analysis. We assume that the participants' deductible choice during rounds 1–7 was unaffected by the following rounds and the change in risk profile, which seems a reasonable assumption because participants were not informed ex ante about this change.

[2] Appendix 3 includes detailed descriptive statistics for each laboratory, balance tests for each laboratory, and t-tests between the two laboratories for the main background characteristics.

[3] Given that the control group could not access any additional information for decision support and the effects of general information on the outcomes considered in the study are all small and insignificant, the IV estimates can be interpreted as average treatment effects on the treated (ATETs) for viewing personalized information. We also replicated the analyses by comparing treatments 2–4 to treatment 1 (general information), excluding the control group, and pooling T1 and the controls, which all provide very similar results, confirming the statement that the general information treatment does not impact the outcomes considered here.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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