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Keita, Moussa

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Moussa Keita, PhD*
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ABSTRACT

The number of mobile health applications has witnessed a soaring during the recent years. According the IMS Institute for Healthcare Informatics, more than 165,000 digital health applications have been available in the Apple iTunes Store and the Android App Store in 2015. Despite the enthusiasm aroused by such a growth, the main concern is the lack of evidence regarding the safety and the efficacy of these devices in terms of health benefits. This study attempts to bring in new insight on this problematic by trying to identify the causal effect of the use of technology on health status. For this purpose, we focus on the specific case of health-tracking applications which are among the most used health applications. Our analysis is based on 1020 subjects suffering from Diabetes and High Blood Pressure to compare the results of those using health-tracking applications to monitor their health and those who are not using these applications. We have estimated the model by Ordinary Least Squares (OLS) and multinomial logit regressions methods. We have also corrected potential selection bias in technology adoption by using the Heckman approach. In terms of results, our estimations show significant positive association between technology use and reported health status and quality of life. In particular, we have found that patients who use digital health-tracking feel better and report better health status than those who do not use them. For example, we have found that HealthApps users are 38 % more likely to achieve "good" health status and are 27% more likely to achieve "excellent" health status as compared to non-HealthApps users. These results appear robust to various sensitivity and robustness checks. However, although its promising nature, the effect of technology identified in this study should be regarded as short-term effect since the configuration of the data does not allow to capture potential *contextual-effect* in health status declaration and possible *novelty-effect* in technology use.

* Centre for Study and Research on International Development (CERDI)
Contact info:
Email : keitam09@ymail.com

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Introduction

The rapid expansion of the mobile technologies that accompanied the advent of high bandwidth Internet connectivity was the catalyst for the emergence of various mobile health-related softwares commonly referred to as "HealthApps". Broadly defined, HealthApps are digital programs which aim to provide consumers/users new forms of interactive healthcare services supported by mobile technologies such as cell phones, tablets, patient monitoring devices, personal digital assistants, and other wireless devices. Among the most widely used HealthApps are those that allow, through sensors, to continuously track and retrieve real-time information on a given health aspect such as heart rate, blood pressure, blood glucose level, body temperature and brain activities, etc. Such information may then be useful both for patients to adapt their personal attitudes and habits concerning their health status and for medical staff to adjust medical practices.

However, despite the surge in the use of these tracking devices in the recent years, little is known about their safety and their effectiveness in terms of health enhancement. Although numerous studies already exist concerning beneficial effects of the Consumer Health Informatics Applications (CHI) in general, studies directed on the impact of the use of new health-tracking devices are very limited if not nearly inexistent. Our study contributes to fill in this gap by using an empirical approach to test whether the use of mobile health tracking applications contribute to improve the general feeling and the quality of life of patients. We gave examined this question by using data on Diabetes and High Blood Pressure patients whose health status has been measured through a self-rated health indicator.

The focus of the study on Diabetes and Blood Pressure diseases is justified by the fact that they are among the most common diseases and the leading causes of death and disabilities worldwide (Lozano et al.,2012; Murray et al., 2012). According to the International Diabetes Federation (2012), the global prevalence of Diabetes mellitus was about 8% in 2011, and is predicted to rise by more than 10% by 2030.

Our analysis is organized as follows. In the first section, we proceed to literature review to present some of the most significant studies that have investigated the link between consumer technology uses and health. In the second section, we present the empirical methodology developed in this paper. We also present the data used as well as some descriptive statistics on the characteristics of the subjects included in the study. The third section is devoted to estimations of the models, presentation and discussion of the results. Lessons learned from this analysis will then allow us to draw a conclusion.

1. Literature review

In empirical literature, the effects of ICT have been examined on several categories of illnesses ranging from addiction problems such as alcohol and tobacco dependency to more severe diseases such as cancer. Most of the empirical studies conducted in this field are based on randomized control trial (RCT) approach which consists in randomly assigning patients to an intervention group and a control group to measure the effects of the program. An extended review of the empirical evidences can be found in Gibbons et al.,(2009). In this section, we present the most significant and more recent studies classified according to the nature of the disease.

Breast cancer

In the recent years, numbers of studies have examined the impact of consumer health informatics applications in the context of breast cancer. For example, studies such as Gustafson et al.(2001) and Gustafson et al.(2008) use data from the Comprehensive Health Enhancement Support System (CHESS) to evaluate the impact of this project on breast cancer participants. Both of these studies found that CHESS intervention has statistically significant positive effects on various aspects such as quality of life, social support, health and information competence of project participants.

Diet, exercise, physical activity, and obesity

Most of the studies that have examined the effect of HCI on diet, exercises, physical activity and obesity have found significant beneficial effects of ICT on health outcomes (Tate et al., 2006; Hurling et al., 2006; Hurling et al., 2007; Haerens et al, 2007; Smeets et al.,2007; etc...). For example, Hurling et al.,(2007), who have analyzed the weekly hours spent sitting by 77 healthy adults have found that a mobile phone technology that delivers an automated physical activity program was associated with greater perceived control and intention to exercise as compared to a control group. Also, Tate et al.,(2006) who have used a sample of 192 adults to investigate the effects of computer-automated tailored and human e-mail counseling in a weight loss program have found significant beneficial effect of technology.

Alcohol reduction and smoking cessation

Among the studies that have examined the impact of technology uses on alcohol reduction and smoking cessation are Cunningham et al.,(2005), Riper et al.,(2008), and Strecher and al.,(2006). For example, Riper et al.,(2008) have used data on 261 individuals with alcohol drinking problems to investigate the effects of a Web-based interactive self-help intervention. They have found that the intervention group decreased significantly their mean weekly alcohol consumption compared to the control group. Also Strecher and al.,(2006) have investigated the effects of a web-based computer-tailored smoking cessation program on a sample of nicotine patch users. They have found significant development in the rate of ten-week continuous abstinence in the intervention group compared to the control group.

Mental health

Studies that have evaluated the impact of CHI on mental health focus on three broad aspects: depression/anxiety, phobia and stress. For example, studies such as Proudfoot et al.,(2004) or Christensen et al.,(2004) have evaluated the impact of Web-based Cognitive Behavioral Therapy (CBT) respectively on 274 and 525 patients with diagnoses of depression and anxiety. The first authors find that the online CBT is associated with significant improvements on the following mental health scale: Beck depression inventory (BDI), Beck anxiety inventory (BAI), Work and Social Adjustment Scale (WSAS). Regarding the second study, it shows that the Web-based CBT was associated with significant improvements in depressive symptoms and dysfunctional thoughts of patients.

Asthma and chronic pulmonary diseases

Many authors have also explored the effects of CHI on pulmonary diseases treatment and management, particularly among children (Jan et al.,2007; Joseph et al.,2003; Krishna et al.,2003; Nguyen et al.,2008; etc.). For example, Joseph et al.,(2003) have evaluated a multimedia Web-based asthma management program targeting 314 urban high school students. Their results indicate that compared to the control group, the intervention group have fewer day and night symptoms, fewer school days missed, fewer restricted activity days and fewer hospitalizations for asthma. Jan et al.,(2007) have used a sample of 164 pediatric patients to evaluate the effect of an Internet-based interactive asthma educational and monitoring program. They have discovered that children in the intervention group experience significant decrease in nighttime and daytime symptoms; but also significant decrease in morning and night peak expiratory flow.

Diabetes and High Blood Pressure

Several studies have also investigated the role of Consumer Health Informatics Applications in Diabetes and HBP problems (Glasgow et al.,2003; Lorig et al.,2006;McKay et al.,2001…). For example, McKay et al.,(2001) have used data on 78 sedentary diabetes patients to evaluate the effects of an Internet-based support to increase their physical activities. Their results indicate that the patients in the intervention group significantly increase their practice of vigorous physical activity and their walking time. Glasgow et al.,(2003) have also used data on 320 type 2 diabetes patients to evaluate the effect of the same program as McKay et al.,(2001). They have reported that the Internet-based support significantly improves the Kristal Fat and Fiber Behavior (FFB) scale and decreases the daily dietary fat consumption, total cholesterol, triglycerides and lipid ratios of the treatment group compared to the control group.

2. Methodology

2.1. Conceptual framework

The main goal of the analysis is to evaluate the additional benefit brought by digital health-tracking over traditional health-tracking methods such as memorization and paper notes. Indeed, according to Fox and Duggan(2013), among the 69% of U.S. adults who track their health indicators in 2012, half of them track their health by memorizing “in their heads”, one third of them keep notes on paper, and one in five use digital technology. It is therefore interesting to quantify the added value of technological tracking comparatively to others forms of tracking and non-tracking. So, to evaluate the effect HealthApps use on the health status, we have built a conceptual framework based on the following equation:

$$H_i = \beta_0 + \beta_1 HA_i + \beta_2 X_i + \varepsilon_i \quad (1)$$

Where H_i represents the health status of subject i. HA_i is the HealthApps use variable. It is a binary variable which takes 1 if the individual i uses mobile HealthApps and 0 otherwise. X_i represents any other characteristic likely to influence health status of individual i. These characteristics include age sex, education and other sociodemographic variables. The coefficients β_0, β_1 and β_2 are parameters to be estimated.

Our main interest parameter is β_1. It captures the benefit of mobile health tracking over non-tracking and others forms of tracking. Since we postulate that mobile HealthApps use exerts positive and significant effect on health status, the coefficient β_1 is expected to be positive ($\beta_1 > 0$). Thiss means that the average health status of the HealthApps users is higher than the average health status of the non-users. The goal of the analysis is to test the statistical significance of this pre-supposed effect.

2.2. Sample

The data used in this study are drawn from the Pew Research Center 2012 heath-tracking database obtained from nationwide telephone interviews of 3,014 adults in the United States. A complete description of this survey is presented in Fox and Duggan(2013).

The respondents have been selected by Random Digit Dialing (RDD) sampling method which consists in generating, at random, telephone numbers that have to be called for the interviews. The advantage of the RDD is that it allows to select phones numbers that are not necessarily present in phones directories, thus avoiding, sampling coverage bias.

The sample selection is done by combining landline and cell phones RDD to reach a representative sample including those who have access to landline and those who have access to cellular telephone. In final, 1,808 landlines and 1,206 cell phones have been selected. The present study is based on 1020 individuals identified as suffering from Diabetes or High Blood Pressure problems. The characteristics of these subjects are described in Table 1.

2.3. Variables and descriptive statistics

Health status

The primary interest variable in this analysis is a self-reported health status assessed on a Likert scale defined from 1 to 4. Self-reported health or Self-rated health (SRH), reflects respondent's subjective sense of health (Snead, 2007). These indicators are commonly used to capture a general sense of health from the perspective of the subjects including both physical and psychological dimensions. They are, generally, constructed through one simple global question asked from the subjects about their overall health status. In this study, the SHR values are obtained from the following question: "*In general, how would you rate your own health?*" The four possible responses to this question are coded as follows: "*1-Excellent*", "2-*Good*", "3-*Fair-only*", "*4-Poor*". However, for methodological concerns, we recoded these values in a way so that low value represents poor health status and high value a better health status. Hence, the final recoding of this variable is: "*1-Poor*", "*2-Fair-only*", "3-*Good*", "*4-Excellent*".

In terms of consistency, the SRH indicators have been found in a number of studies as reliable and valid measure of health status (see for example Snead, 2007; Krause and Jay,1994; Lundberg and Manderbacka,1996; Miilunpalo et al,1997; Idler and Benyamini,1997; Ware and Gandek,1998; Fayers, 2005; Subramanian et al,2010)

HealthApps use

Our second interest variable is the HealthApps use. During interviews, the respondents were asked if they had any digital application on their mobile phone they used to track any indicator related to their health. Based on the answers to this question, two groups of subjects have been distinguished: those who use mobile digital applications to track their health status and those who do not use mobile Apps. The goal of our study is to analyze, through adequate statistical methodology, the average health status of the first group compared to the average heath status of the second group. However, it should be noted that the simple categorization of individuals based on the use of Health Applications from the mobile phones rise some methodological issues that will be discussed later.

Control variables

In order to capture other factors that affect heath status independently from mobile technology use, several control variables have been added to the model. These control variables include age, sex, education, marital status, labor market status, health insurance coverage, family income categories, race and ethnicity. Most of these variables are found in the literature as significant determinants of health status (see for example Subramanian et al,2010; Allen et al.,2016; Bora and Saikia,2016; Shawel et al., 2016; Bryla et al.,2016).

Table 1 below presents the descriptive statistics on the main interest variables of the study as well as comparative statistics on characteristics of HealthApps users and non-HealthApps users. We can see that the average health status of individuals in the sample is 2.66. This value appears slightly above the central value of 2 in the sense that health status has been rated on a scale defined from 1 to 4. Also, since the calculated statistics were weighted by sample weights, this average value of health status is also representative of all individuals in the general population with the same characteristics as those in the sample.

Regarding the comparison between HealthApps users and non-HealthApps users, we see that the average health status in the first group is 2.82 with a standard deviation of 0.86, while the average health status in the second group is 2.65 with a standard deviation of 0.83. Therefore, health status seems relatively better in the first group compared to the second group. This is confirmed by the pvalue the Student test presented in the fourth column of Table 1 which indicates that the difference is significant at 1% level. The challenge of our analysis will be to determine to -what extent this difference can be attributed totally or partially to the use of digital technology.

Table 1 : Descriptive statistics

	Overall	Health Apps users (5.7%)	Non-Health Apps users (94.3%)	Pvalues t-test (diff. in means and proportions)
self-rated health score mean(±sd) (min-max)	2.66 (±0.83) (1-4)	2.82 (±0.86) (1-4)	2.65 (±0.83) (1-4)	0.001
Age (in years) mean(±sd) (min-max)	58.31 (±15.12) (18-95)	47.61 (±12.16) (24-80)	58.98 (±15.05) (18-95)	0.000
Sex (% Male)	44.50	41.29	44.44	0.297
Marital status (in %)				
single	11.98	19.03	11.54	0.000
union	58.76	66.00	58.92	0.018
divorced	12.07	3.06	12.12	0.000
separated	3.32	5.94	3.19	0.012
Widowed	12.99	5.96	13.28	0.000
unreported status are omitted				
Education levels (in %)				
primary education	6.76	0.99	7.19	0.000
secondary education	43.88	28.32	44.44	0.000
tertiary education	48.59	70.69	47.57	0.000
Labor market status (in %)				
Working/employed	37.75	75.52	35.81	0.000
disabled	14.75	7.93	14.86	0.001
retired	36.07	8.51	37.56	0.000
student	14.75	7.93	14.86	0.001
Other categories are omitted				
Health insurance coverage (in %)				
Has health insurance	88.61	96.92	88.23	0.000
Family income categories (in %)				
Less than $20,000	25.85	15.50	26.33	0.000
]$20,000- $40,000]	21.47	15.03	21.93	0.006
]$40,000- $50,000]	8.47	10.03	8.38	0.329
]$50,000- $75,000]	9.24	17.62	8.87	0.000
]$75,000- $100,000]	6.73	6.00	6.77	0.614
More than $100,000	28.24	35.83	27.73	0.003
Ethnicity (in %)				
black	15.32	23.27	14.72	0.000
hispanic	9.42	12.70	9.22	0.050
Nb of observations	1020	58	962	
Nb of weighted observations	5226	286	4940	

Statistics presented are the weighted values.

On can also note that despite the current development of technology, the rate of HealthApps use is still very low, since only 5.7% of the individuals in our sample use these applications against 94.3 who do not use them. At first glance, such an adoption rate may seem very low.

However, taking into account the age of the individuals in the sample, this rate of adoption is relatively normal and reflects the degree of appetence for this category of population to new technologies.

Indeed, as one can see from Table 1, the average age of individuals in the sample is 58.31 years with a significant difference between HealthApps users (47.61 years) and non-HealthApps users (58.98 years). The fact that individuals in the sample are relatively old is consistent with the study object as it focuses only on subjects suffering from Diabetes and High Blood Pressure (HBP) problems. It is widely recognized that high prevalence of these types of diseases are predominantly found among older people. So, the coincidence between high average age, high prevalence of Diabetes and HPB and low technology use is not fortuitous. This tends to support the validity of our analysis sample.

Finally, the statistics presented in Table 1 tend to suggest that HealthApps users and non-HealthApps users are different in their characteristics, especially in terms of marital status, education, income, etc. (see Table 1). Therefore, the estimation strategy should take into account this dissimilarity between the two groups in order to correctly identify the causal effect of technology use.

3. Empirical strategy

3.1. Estimation and results

We estimate equation (1) by conducting Ordinary Least Squares (OLS) estimation in which the dependent variable is health status and the independent variable is the HealthApps use supplemented by other control variables. The results of the estimation are presented in Table 2 below.

Table 2: Results of OLS estimation
(dependent variable is health status)

Variables	Coefficients estimates	Robust standard	Student t	Pvalue
HealthApps use	-0.078	0.033	-2.388	0.017**
age	-0.010	0.006	-1.667	0.096*
Sex				
male	0.019	0.023	0.826	0.409
Ref =Female				
Education				
secondary_level	0.071	0.031	2.315	0.021**
tertiary_level	0.173	0.048	3.604	0.000***
Ref =Primary level or Less				
Marital status				
single	-0.004	0.038	-0.105	0.916
divorced	-0.088	0.036	-2.444	0.015**
separated	0.070	0.063	1.111	0.267
Widowed	-0.106	0.037	-2.865	0.004***
Ref = married or in union				
Labor market status				
retired	-0.103	0.060	-1.717	0.086*
disabled	-0.066	0.032	-2.038	0.042**
Ref = employed/working				
Health insurance coverage				
has_health_insurance	0.317	0.148	2.142	0.032**
Family income				
]$20,000- $40,000]	0.233	0.099	2.354	0.019**
]$40,000- $50,000]	0.532	0.046	11.565	0.000***
]$50,000- $75,000]	0.561	0.045	12.467	0.000***
]$75,000- $100,000]	0.719	0.051	14.098	0.000***
More than $100,000	0.799	0.049	16.306	0.000***
Ref = Less than $20,000				
Ethnicity				
black	0.125	0.064	1.953	0.051*
hispanic	-0.137	0.059	-2.342	0.019**
Ref = non black/non hispanic				
Constant	2.449	0.078	31.397	0.000***

Adjusted R2=0.132 ; F stat=37.561 Global Significance=0.000;
N. subjects=1017 ; N. Weigthed observations=5036

Coef. significance levels *** p<0.01, **p<0.05, *p<0.10

Before moving on to discussion of the results concerning our main interest variables, it is necessary to briefly discuss about the results on the control variables. As one can see from Table 2, the coefficients on the control variables appear, in most cases, significant and with expected sign. For example, the results show that health status decreases significantly as age increases. This association is significant at 10% level. It also appears that education is significantly correlated with health. The results show that more educated people have significantly higher health status. This result is confirmed by the significance of the coefficients associated with secondary and tertiary education levels. More specifically, these coefficients indicates that people with secondary and tertiary education have, in average, good health status than those who have primary education or less. This effect seems to be linear since the magnitude of the coefficient on tertiary education is higher than that of the coefficient on secondary education level. This means that the effect of education on health increases with education level.

Regarding other control variables such as income, we find, for example, that health status is positively and significantly associated with income level. The health status is significantly higher for people living in high income families compared to those living in low income families. This effect also appears to be linear since the magnitudes of the coefficients increase with income levels. Other variables such as health insurance coverage, labor market status and ethnicity also appear significant and with expected signs. However, no gender effect cannot be identified. Indeed, although the coefficient on sex variable is positive, the student test show that there is no significant difference between men and women in average health status. This result appears contrary to those in other studies such as Bora and Saikia(2016) who have found that the relative risk of reporting poor health is significantly higher for women than men. However, overall, the results obtained on the control variables remain consistent with those in numerous studies found in the literature (eg. Subramanian et al.,2010; Allen et al.,2016; Bryla et al.,2015).

Turning now to the effect of HealthApps, results in Table 2 show, very surprisingly, negative and significant association between mobile health-tracking and health status. This result contradicts the intuition that has emanated from Table 1 where the gross comparison has showed that average health status is higher among HealthApps users than non-HealthApps users. The negative coefficient identified from OLS estimation tends to suggest the opposite by showing that HealthApps use have an adverse effect on health status. However such a result can, potentially, be the reflection of estimation bias caused by the existence of a selectivity in the decision to adopt mobile technologies.

Indeed, theoretically, selection bias have, potentially, two sources: the difference between the two comparison groups in their observable characteristics and the difference in their unobservable characteristics. The first possibility is supported by the statistics presented in Table 1 which show a clear and significant difference between HealthApps users and non-HealthApps users on characteristics such as age, education level, income level, etc. This difference may well be the cause of the bias when it is not taken into account during estimations. But since these variables are already included in the model as control variables, selection bias that may come from these characteristics is considerably reduced. Therefore, the only potential source of selection bias is difference in unobservable characteristics, especially those influencing both health status and the decision to adopt a health-tracking technology.

The major consequences of selection bias on unobservables is the reverse causality problem in which technology use influences health status and health status, in return, influences the decision to adopt technology.

For example, one may think that individuals with more deteriorated health status are the more likely to use technology devices to monitor their health status. Therefore, the decision to adopt mobile technologies is more likely to be motivated among subjects with low health status than subjects with better health. Such a hypothesis is supported for example by Fox and Duggan (2013) who have shown that people living with chronic conditions are more likely to track their health indicator or symptoms. Thus, a precise estimate of the impact of mobile health-tracking on the health status requires correction of selection bias.

In this study, we adopt the correction procedure proposed by Heckman(1979). The Heckman correction method is a two-step procedure in which the decisions of adoption of technology is modeled through probit regression to construct a selection bias control factor (first step). This correction factor is then included in the health equation estimation (second step) to produce unbiased estimates.

The first step of the Heckman procedure corresponds to the estimation of the selection model to modelize the process underlying the decision of HealthApps adoption. In the estimation of this selection model, the dependent variable is a binary variable indicating whether or not the subject uses mobile health tracking applications. To modelize this decision, we choose two additional variables in addition to the independent variables already present in the analysis to capture the technology propensity of individuals. The first variable is mobile phone ownership. As mobile phone ownership is a necessary (but not sufficient) condition to use mobile HealthApps, respondents were asked during the interview if they own a cell phone independently of its degree of sophistication. Assuming that cell phone ownership is a pre-condition for HealthApps use, we create a dummy variable taking 1 if the respondent has mobile phone and 0 otherwise. The second decision variable is frequent Internet use by the respondents. We assume that people who frequently use Internet are those who are more likely to adopt a mobile health technologies. In our analysis sample, 63.5% of the respondents own cell phones while 36.5% do not. And 63.6% of respondents use frequently Internet while 36.5% do not use at all. It also appears that mobile phone ownership and Internet use are strongly correlated. The pvalue of chi2 test we have run between the two variables is 0.000 and the value of Cramer's V is 0.429 significant at 1% level. Therefore, by combining cell phone ownership and frequent Internet use variables with the other independent variables present in the model (such as age sex, education), one can accurately estimate the technology propensity of the respondents. Results of estimation of this selection process are presented in Table 3 below.

In these estimation, as initially expected, results show significant positive association of mobile HealthApps adoption with cell phone ownership and frequently Internet use. We find that the adoption is also positively correlated with education and income levels. In contrast, HealthApps adoption is found to be negatively associated with age, which means that technology adoption is significantly low among the elderly (see Table 3).

Table 3: Results of probit estimation
(Dependent variable is the decision to adopt HealthApps)

Variables	Coefficients estimates	Robust standard errors	Wald Chi2	Pvalue
Cellphone owner	0.516	0.231	4.985	0.026**
Internet user	0.832	0.339	6.023	0.014**
age	-0.034	0.007	23.592	0.000***
Sex				
Male	-0.068	0.120	0.321	0.571
Ref =Female				
Education				
secondary_level	0.411	0.138	8.87	0.003***
tertiary_level	0.410	0.190	4.657	0.031**
Ref =Primary level or Less				
Marital status				
single	0.164	0.188	0.761	0.383
divorced	-0.203	0.256	0.629	0.428
separated	0.103	0.378	0.074	0.786
Widowed	0.441	0.240	3.376	0.066*
Ref = married or in union				
Labor market status				
retired	-0.343	0.182	3.552	0.059*
disabled	-0.379	0.263	2.077	0.150
Ref = employed/working				
Health insurance coverage				
has_health_insurance	-0.049	0.267	0.034	0.854
Family income				
]$20,000- $40,000]	0.955	0.424	5.073	0.024**
]$40,000- $50,000]	0.953	0.439	4.713	0.03**
]$50,000- $75,000]	0.172	0.071	5.931	0.015**
]$75,000- $100,000]	0.892	0.448	3.964	0.046**
More than $100,000	0.150	0.439	0.117	0.732
Ref = Less than $20,000				
Ethnicity				
black	0.128	0.052	6.059	0.014**
hispanic	0.139	0.078	3.143	0.076*
Ref = non black/non hispanic				
Constant	0.114	3.467	0.001	0.975
Pseudo R2=0.421 ; Chi2=451.189 Global significance=0.000; N. subjects=1017 ; N. Weighted observations=5036				
Coef. significance levels *** p<0.01, **p<0.05, *p<0.10				

The residuals obtained from the probit estimation are used to construct the Inverse Mill's Ratio which represents the correction factor. This factor commonly called “Lambda” captures the effects of all unobserved characteristics related to technology adoption decision. This variable is included in the second stage estimation to control the selection bias. The results of the new estimations of the health equation are presented in Table 4 below.

Results obtained from estimation of corrected model show positive and significant association between HealthApps use and the health status. The significance of the coefficient associated with the correction factor Lambda confirms the presence of selection bias, thus justifying, the relevance of the corrective procedure.

Regarding the control variables, coefficients and significance remain substantially the same as in the first estimations. We observe positive association of education and income with health status. Conversely, we observe negative association between age and health status while the effect of gender is not significant.

Table 4: Results of OLS estimation with control of selection bias
(dependent variable is health status)

Variables	Coefficients estimates	Robust standard errors	Student t	Pvalue
HealthApps use	0.220	0.111	1.982	0.048**
age	-0.698	0.305	-2.289	0.022**
Sex				
male	-0.013	0.028	-0.464	0.643
Ref =Female				
Education				
secondary_level	0.030	0.015	2.034	0.042**
tertiary_level	0.244	0.063	3.873	0.000***
Ref =Primary level or Less				
Marital status				
single	-0.125	0.069	-1.814	0.07*
divorced	-0.112	0.046	-2.435	0.015**
separated	0.159	0.118	1.347	0.178
Widowed	-0.007	0.003	-2.333	0.02**
Ref = married or in union				
Labor market status				
retired	-0.035	0.014	-2.500	0.012**
disabled	-0.134	0.044	-3.059	0.002***
Ref = employed/working				
Health insurance coverage				
has_health_insurance	0.145	0.062	2.324	0.02**
Family income				
]$20,000- $40,000]	0.127	0.063	2.016	0.044**
]$40,000- $50,000]	0.562	0.056	10.036	0.000***
]$50,000- $75,000]	0.495	0.063	7.857	0.000***
]$75,000- $100,000]	0.516	0.065	7.938	0.000***
More than $100,000	0.637	0.061	10.443	0.000***
Ref = Less than $20,000				
Ethnicity				
black	-0.166	0.088	-1.886	0.059*
hispanic	-0.110	0.077	-1.438	0.151
Ref = non black/non hispanic				

Constant	1.812	0.108	16.778	0.000***
Correction factor Lambda	0.068	0.017	4.000	0.000***
Adjusted R2=0.183 ; F stat=35.632 Significance=0.000; N. subjects=1017 ; N. Weighted observations=5036				
Coef. significance levels *** p<0.01, **p<0.05, *p<0.10				

3.2. Sensitivity diagnostics

To test the sensitivity of our results to various estimation condition, we conduct a diagnostic test consisting in estimating a multinomial logit model instead of OLS estimation. Indeed, since the health status variable we use is defined on a limited number of values (from 1 to 4), we can consider each value as a category and then estimate the probability that an individual has to be in one of four categories.

The OLS estimation consider health status as defined on a continuous scale. This means, for example, that switching from status 1 to the status 2 would be equivalent to switching from the state 2 to state 3 or even from state 3 to state 4. Which is to say that OLS estimation gives the same weights to every unit changes in health status. The advantage of using a multinomial logit model in this situation is to consider each value of the health status as a specific category. Such an approach has been used in other studies such as Bryla et al.(2015).

Thus, treating health status as a categorical variable, equation 1 is estimated using multinomial logit regression while correcting the selection bias. Results of this estimation are shown in Table 5 below.

Table 5: Results of multinomial Logit estimation
(dependent variable is health status defined by category)

Variables	Categorical health status		
	Fair (29.7 %)	**Good (47.6%)**	**Excellent (13.6%)**
	Odds Ratio	**Odds Ratio**	**Odds Ratio**
HealthApps use	1.16 [0.139]	1.38 [0.024]**	1.27 [0.067]*
age	1.65 [0.012]**	0.99 [0.046]**	0.96 [0.000]***
Sex			
Male	1.07 [0.648]	0.93 [0.629]	0.90 [0.555]
Ref =Female			
Education			
secondary_level	0.68 [0.137]	1.80 [0.04]**	0.89 [0.744]
tertiary_level	1.23 [0.467]	2.08 [0.019]**	1.52 [0.063]*
Ref =Primary level or Less			
Marital status			
single	1.11 [0.675]	0.71 [0.179]	0.58 [0.011]**
divorced	0.63 [0.027]**	0.75 [0.146]	0.4 [0.002]***
separated	0.38 [0.068]*	0.98 [0.97]	1.68 [0.43]
Widowed	0.55 [0.007]***	0.98 [0.928]	0.47 [0.006]***
Ref = married or in union			
Labor market status			
retired	1.77 [0.002]***	1.62 [0.084]*	0.71 [0.016]**
disabled	0.74 [0.129]	0.69 [0.053]*	0.38 [0.003]***
Ref = employed/working			
Health insurance coverage			
has_health_insurance	1.57 [0.174]	1.6 [0.024]**	2.1 [0.002]***
Family income			
]$20,000- $40,000]	1.98 [0.013]**	2.16 [0.000]***	2.31 [0.006]***
]$40,000- $50,000]	1.68 [0.054]*	2.23 [0.008]***	2.48 [0.017]**
]$50,000- $75,000]	1.77 [0.016]**	2.35 [0.009]***	2.72 [0.014]**
]$75,000- $100,000]	1.82 [0.004]***	2.94 [0.020]**	2.98 [0.041]**
More than $100,000	1.83 [0.028]**	3.1 [0.065]*	3.57 [0.053]*
Ref = Less than $20,000			
Ethnicity			
black	1.25 [0.035]**	0.92 [0.679]	0.37 [0.001]***
hispanic	1.95 [0.007]***	1.01 [0.972]	0.96 [0.904]
Ref = non black/non hispanic			
Constant	0.8 [0.644]	0.86 [0.764]	0.70 [0.604]
Correction factor Lambda	Yes	Yes	Yes

Pseudo R2=0.291 ; Chi2=1045.163 Global significance=0.000;
N. subjects=1017 ; N. Weighted observations=5036
Reference health status is "Poor" (9.1%).

Pvalues in brackets; Significance levels *** p<0.01, **p<0.05, *p<0.10

Although results from the multinomial Logit estimation do not differ fundamentally from those in OLS estimations, some interesting elements can be noted in this sensitivity analysis. The first is the differentiated effects of covariates according the categories of on health status.

First, regarding the HealthApps use variable, we find that HealthApps users have greater probability to reach high level of health status than non-HealthApps users. The Odd-ratios obtained on this variable show, for example, that HealthApps users are 1.38 times more likely to achieve "good" health status and 1.27 times more likely to achieve "excellent" health status compared to non-HealthApps users. These respectively represent 38% and 27% of difference in probabilities between the two groups of comparison. These results thus tend to confirm the existence of a significant beneficial effect of health applications on health status.

Regarding the control variables, it appears, for example, that people with secondary education are more likely to have a "Good" health status while people with tertiary education are more likely to have either a "Good" or an "Excellent" health status. Concerning the effect of income category, the estimations confirm the linearity of the effect of income category on health status. The higher the income level, the more probable to be in higher heath category. For example, we can see that an individual living in a family whose income is higher than US$ 100,000 has a 3.57 times higher probability to reach an "Excellent" health status than that of an individual living in a family whose income is lower than $ 20,000. Which is to say that "In God, the American certainly does trust. But, he also knows that dollars can make miracles".

3.3. Robustness check

In addition to the sensibility test, we also conduct a robustness check to appreciate the solidity of the results. The robustness check consists, here, in replacing self-rated health status variable by self-rated quality of life in the estimation equations.

The self-rated quality of life is a more general health indicator capturing either physiological and psychological health dimensions but also socioeconomic dimensions. As for the self-rated health status, the self-rated quality of life indicator used here has been constructed from a simple synthetic question during interviews formulated as follow: "*Overall, how would you rate the quality of life for you and your family today?*" The possible answers were coded initially as: "*1-Excellent*", "*2-Very good*", "*3-Good*", "*4-Fair*" and "*5-Poor*". These values have been recoded in such a way that level 1 represents poor quality of life while level 5 represents excellent quality of life.

The results of the estimations (OLS and MLOGIT) obtained by using this variable are shown in table 6 below.

As we can see from Table 6, the replacement of the health status by the quality of life does not modify the meaning of the results. The OLS estimation shows positive and significant impact of HealthApps use on the continuous score of quality of life while the multinomial logit estimation shows significant impact on the occurrence of "Very Good" and "Excellent" quality of life. This constitutes additional empirical arguments on the robustness of the results. They contribute to reinforce the idea that mobile health-tracking technology has undeniably a significant beneficial effect in terms of improvement in health and quality of life of patients suffering Diabetes and high blood pressure problems.

Table 6: Results of OLS and multinomial Logit estimations
(dependent variable is quality of life)

	OLS	**Multinomial Logit**			
		Categorical scores			
	Continuous score	**Fair (20.5 %)**	**Good (39.3%)**	**Very Good (20.8%)**	**Excellent (9.9%)**
Variables	**Coefficients**	**Odds Ratio**	**Odds Ratio**	**Odds Ratio**	**Odds Ratio**
HealthApps use	0.67 [0.03]**	1.27 [0.10]*	1.17 [0.32]	1.57	1.13
age	-1.03 [0.09]*	1.25 [0.35]	0.99 [0.06]*	0.97	0.96
Sex					
Male	-0.07 [0.06]*	0.84 [0.26]	1.06 [0.67]	0.73	0.74 [0.09]*
Ref =Female					
Education					
secondary_education	0.05 [0.02]**	1.02 [0.93]	1.15 [0.08]*	1.75	0.81 [0.55]
tertiary_education	0.19 [0.03]**	1.57	1.37	2.23	1.56
Ref =Primary level or Less					
Marital status					
single	0.15 [0.11]	1.12 [0.73]	1.56 [0.15]	0.9 [0.01]	0.51 [0.07]*
divorced	-0.2	1.04 [0.86]	0.52	0.91 [0.67]	0.51
separated	-0.35 [0.14]	1.3 [0.63]	0.84 [0.76]	0.81	0.43 [0.32]
Widowed	-0.11	1.23 [0.39]	1.33 [0.19]	0.64 [0.06]*	0.89 [0.71]
Ref = married or in union					
Labor market status					
retired	-0.15 [0.12]	1.38 [0.10]*	1.14	0.77	0.54 [0.01]
disabled	-0.27	1.32	0.43	0.47	1.12 [0.71]
Ref = employed/working					
Health insurance coverage					
has_health_insurance	0.15 [0.08]*	2.41	1.81	2.13	1.12 [0.75]
Family income					
]$20,000- $40,000]	0.11 [0.06]*	1.17	1.24	2.26	1.01 [0.97]
]$40,000- $50,000]	0.08 [0.04]**	1.32	1.32 [0.01]	2.44	1.22 [0.59]
]$50,000- $75,000]	0.66	1.44	1.53	2.52	1.18 [0.73]
]$75,000- $100,000]	0.44	1.71	2.21	2.63	1.28 [0.73]
More than $100,000	0.69	2.01	2.52	2.74	1.36 [0.66]
Ref = Less than $20,000					
Ethnicity					
black	-0.14 [0.25]	1.06 [0.61]	1.11 [0.65]	0.57	0.93 [0.79]
Hispanic	-0.24	1.13 [0.66]	0.86 [0.6]	0.41 [0.01]	0.58 [0.09]*
Ref = non-black/non-hispanic					
Constant	1.61	0.78 [0.65]	0.87 [0.78]	0.63 [0.44]	0.59 [0.46]
Correction factor	Yes	Yes	Yes	Yes	Yes
Models statistics	Adj R2 =0.14	Pseudo R2=0.265 ; Chi2=968.599 Sig.=0.00;			
	N. subjects=1017 ; N. Weigthed observation=5036				
	Reference quality of life is "Poor" (9.5%).				

Pvalues in brackets ;Significance levels *** p<0.01, **p<0.05, *p<0.10

Conclusion

Results obtained in this study provide solid empirical evidence on the causal effect of the technology use on health and quality of life. We find that Diabetes and High Blood Pressure patients who use health-tracking technologies feel better and have better health status than those who do not use technology. This result appears robust to numerous sensitivity and robustness checks. Theoretically, this result can be explained by the fact that technology provides patients with reliable information about their health and direct assistance allowing them to increase their involvement in the monitoring and treatment of their disease.

In light of the results obtained in this study, the development of HealthApps constitutes a credible way to expand the supply of healthcare services that will be beneficial not only for patients but also for healthy people as well as for the whole health system. For that, we consider that health-tracking applications, on which is focused this study, should have an entire place in the mHealth, the new healthcare paradigm services supported both by national and international agencies.

Although promising, the results obtained in this study should, however, be interpreted with some caution. Indeed, despite the solidity of the methodological tools used in this work, our methodology potentially suffers from several shortcomings. In this respect, the first limitation is the fact that the study is conducted on cross-sectional data. One of the major disadvantages cross-sectional data is their inability to account for temporal dimensions on the phenomenon under study. In our case, the use of cross-sectional data has two implications. The first is the impossibility to control contextual effects. Indeed, given that the analysis is based on Self-Rated Health and Self-Rated Quality of Life, the values reported by an individual may be influenced by its present living condition and environment. When the current environment is favorable, individual will tend to report higher values and when the context is unfavorable he will tend to report lower values. Therefore, to be able eliminate such a contextual effect, longitudinal data are needed.

The second implication of the use of cross-sectional data is the impossibility to eliminate the *novelty-effect* associated with the use of a technology device. Indeed, a user who has installed a new application on his smartphone will tend to use it with assiduity. But with time, this novelty-effect disappears gradually. Therefore, to identify the effect of the application beyond this novelty-effect, it is necessary to follow the user over time. Since such an analysis is conducted only in presence of longitudinal data, the effects identified in this study should be considered, first, as short-term effects. Identification of long-term effects will require further investigation.

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