Consumerism in online health information search and self-tracking devices

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Abstract

The Internet hosts a plethora of health information and has become a popular source users turn to when looking up information. Nonetheless, the existence of this wealth of online health information generates challenges related to access and user skills. Whereas previous studies surveyed a cross-section of users, our aim is to complement them with a population-level study. We use nationally representative data collected by Statistics Finland between 2006-2016 to investigate the extent to which online health information search and use of self-tracking devices associate with social, economic, and demographic factors. We have used descriptive statistics and logistic regressions to show that, in 2016, disparities still existed in how Finns make use of the health information found online as well as appropriate new devices such as self-tracking devices. The population level of this study aids us in understanding the degree of adoption of new technologies used by different demographics. We show that, despite having access to the Internet, certain factors influence actual usage negatively. Looking forward, a key limitation of our study is a lack of measures to determine how these demographics use health information to adjust their behaviour. In the Nordic context, important research implications relate to the persisting digital divides in health technology adoption.

Keywords: online health information, self-tracking devices, technology adoption, digital inequality

Introduction

The Internet is a manifold source of health information and a common go-to resource for patients and consumers (Fiksdal et al., 2014). Nonetheless, online health information availability also contributes challenges related to access (owning a device with which to surf online and a working Internet connection) as well as user skills. In addition, the relevance of the information found online for the individual user is particularly important. When searching for health information online, users undertake several actions, amongst others they filter and compare results until they achieve information saturation (Fiksdal et al., 2014); they assess whether the information they came across originates from a credible source (Hajli et al. 2015; either health-care provider or peer experience, Hayat et al., 2017); they determine whether it aids themselves with self-diagnosis (Larner, 2006) or prepares them for an encounter with their physician (Dolan et al., 2004).

Consumerism changes the relationship between professionals and *clients*, who take an active interest and responsibility for their welfare (Jaakkola & Halinen, 2006; Gallan et al., 2013; Hajli, 2014). Interest may manifest as health consumerism and includes information gathering from available sources, including the Internet, to self-diagnose or in preparation to seeking advice from health care providers. Increasingly, health plans move beyond information provision and consumption to include individual's lifestyles (McColl-Kennedy et al., 2012). Gould and Gould (2011) also found that people regard health as a consumption object, patterned by social grade and gender. With information availability on the Internet rising, the relation between individuals and health-care professionals needs to be redefined to account for the change in information asymmetry, essentially turning care patient-oriented (Taylor, 2009; Andreassen, 2012). Health information seeking behaviour 'refers to the ways in which individuals seek information about their health, risks, illnesses, and health-protective behaviours' (Jacobs et al., 2017: 2)Health is highly individualized (McGregor, 2001) and studies of health information seeking online focus on individuals' behaviours and preferences (Koch-Weser et al., 2010; McColl-Kennedy et al., 2012; Jacobs et al., 2017). In contrast, Dagevos and colleages (2010) note that in the Chinese case, asking neighbors, kin and the elderly for health related information are deeply embedded in the social fabric. Three items ("When I have health problems, I seek my neighbors' opinion", "I keep to the norms of a healthy life as taught by my mother, mother-in-law and grandma", "I listen to the opinions of old people about healthy lifestyle") correlate among themselves forming a principal component termed 'group conformity' (Dagevos et al., 2010: 14). Thus, gaining access to health information is inasmuch a matter of the source of information as it is of cultural preferences.

In the context of growing availability of health related information, retrieval and interest from consumers has also risen across the world. Figure 1 shows the trend of health information search on the Internet in Finland among the adult population. Overall, there has been a 12 point increase (57 to 69 %) in the percentage of individuals who have sought information related to diseases, nutrition, and health on the Internet between 2006 and 2016. Nonetheless, there have been two inflection points, in 2009 and 2014 respectively, when more individuals sought out health related information online.

<Figure 1 Health information search on the Internet, 2006-2016 (%). Source: OSF (2017)>

Note: Data for 2012 not available.

The relevance of health information search behaviour on the Internet is influenced by the degree to which the searcher identifies with the content found. In effect, people search for health information written by people like themselves (Sillence et al. 2007). Relating to others with similar medical conditions strengthens the feeling of community online (Cotten & Gupta, 2004). Online peer communities and social media tools enable individuals to provide and receive health information and emotional support, while simultaneously reducing the costs of health care providers and improve services (Hajli, 2014). Patients with similar health conditions connect with each other using online support or peer groups, essentially sharing their knowledge and experiences and producing 'value' for others. 'Contact with fellow patients advances self-education and individual responsibility, encourages initiative and gives people an opportunity to help others' (Alpai et al., 2011: 250).

An early study found that most patients (68%) preferred to consult their general practitioners, compared to 6% who preferred the Internet as the primary source of health information (Dolan et al., 2004). Also Alpai and his colleagues (2011) caution that individuals need to be critical about the information they receive from non-professionals. Hayat and colleagues (2017) found that finding peers online with similar conditions moderates health outcomes. In addition, the study stressed the importance of finding peer support offline, in terms of helping users with lower skills navigate the online health environment, and its influence on perceived health outcomes (Hayat et al., 2017).

The Internet and online communities are not exclusive sources of user-generated health information. Nowadays, emerging technologies such as smartphone applications, activity wristbands or smart watches enable the collection, analysis, sharing and behaviour adjusting of the consumers using such technologies. Instead of accessing and finding value in information sourced by others, these self-tracking technologies provide information about oneself thereby increasing the credibility and relevance of the information. These technological advancements serve well the consumeristic approach to medical information discussed in the literature (Jaakkola & Halinen, 2006; Gallan et al., 2013; Hajli, 2014), while at the same time portray the consumer as an ‘active’ facilitator of their own well-being. In addition, users of these technologies can purposely share the information gathered with third parties (on social media, for instance) yet equally important it is to stress that these technologies also have unintended consequences when used, such as those related to individual privacy (Harrison et al., 2007).

Linking health information search to outcomes associated with enhancing health opportunities such as physical activity has been the subject of much research (e.g. Amante et al. 2015; Miriovsky et al. 2012). Smart watches, wearable computers worn on the wrist that give access and notifications of personal information, have only recently been introduced as ‘preventive health tool’ for users (Yoon et al., 2015). Wearables, smart watches particularly, are poised to significantly impact consumers’ daily lives, despite the fact that consumers are unaware of the benefits of using them (Cecchinato et al., 2015).

Compared to many other information and communication technology (ICT) devices, such as smartphones, tablets, and desk-top computers, smart watches are physically closer to the user’s body and capable to measure its activities and location due to array of sensors (Rawassizadeh et al., 2014). Chiefly, smart watches track users and collect data on location, the steps they have taken, distances walked or ran, calories burned, sleep tracking, or heart rate – properties that make them a boon to mobile health technologies (Rawassizadeh et al., 2014). Compared with fitness trackers, smart watches both collect fitness data as well as perform basic mobile phone communication functions, which often limits the battery life. In this article, we do not discriminate between the two but rather view them as a single device collecting and measuring users’ body function.

Nonetheless, for our purposes, the use of smart devices for fitness rather than managing serious diseases is important as it helps the users monitor themselves rather than receiving tailored medical solutions (Li et al., 2016). Overall, the academic literature on smartwatches is ‘technology driven’ as Choi and Kim (2016) put it, focusing on the use purposes. For instance, features inherent in the system or customized by the user, which are included in technologies used for health monitoring have been discussed (Yoon et al., 2015; Portz et al., 2016). While surveying smartwatch users, Yoon and his colleagues (2015) found that users were skeptical about the accuracy of the information gathered and its use for health management. Their study also found a need to provide hybrid features (tailored within the software and user-initiated) as well as data sensitivities regarding health data privacy.

Dolan et al. (2004) found small differences by gender but considerable differences according to age among individuals who used the Internet for health information. Socio-demographic factors including age, gender, income and education and their persistence over time influence health information seeking (Cotton & Gupta, 2004; Beaudoin & Hong, 2011). The implicit idea is that the presence of common socio-economic resources strongly affects the types of lifestyle and Internet use patterns people are able to engage in. In the simplest sense, this means that there are differences between groups of people, for example when it comes to their interests, skills of taking advantage of available information or avoiding risks with the use of the information. Moreover, educated people seek more health-related material online (Jacobs et al., 2014; Osei-Frimpong, Wilson & Lemke, 2018).

Similar assumptions connect with the use of health technology devices. For instance, tailoring health information has been proposed as a way of addressing the skills gap produced by information technologies (Alpai et al., 2011). Competencies regarding the acquisition of relevant knowledge, own data interpretation and use for self-management of health is deemed important. Users' perceived benefit of wearables is influenced by how informative they think such wearables are (if they provide relevant health information about the user) as well as their comfort, durability, and price (Li et al., 2016). The perceived benefit is also influenced by perceived privacy risk, and both variables influence adoption intention positively and negatively, respectively. These notions are in line with previews studies concerning the socio-demographic differences in technology adoption (Räsänen 2008; Van Deursen & Van Dijk, 2014 a,b).

It appears that certain demographic subgroups are more likely to recognize the benefits of the technology, which translates into increased probability of using them. In addition, those individuals with economic restrictions cannot always buy new products even though they would like to do so (see for instance the discussion on material access in van Dijk, 2005). Against this background of health consumerism, the purpose of this study is two-fold. First, our aim is to study online health information search and use of self-tracking devices in Finland, a country with extended health care provision, Internet access and Internet literacy. Second, we aim to understand which demographic factors associate with health information search online and use of self-tracking devices, and whether these overlap or digress for the different activities. There is little knowledge on how individuals perceive and intent to use such innovations especially in the Nordic context.

Research Questions

In this article, we focus on how Finns manage health-related information. We determine if and how differences occur in time when searching for health related information using the Internet compared to using smartwatches to track one's own performance. We then proceed to analyze the predictors of these differences. We elaborate the following research questions:

RQ1: To which extent do sociodemographic and economic determinants associate with health information management outcomes, such as searching for health information online or wearing a self-tracking device?

RQ2: Are the differences in demographic factors consistent across the two outcomes, searching for health information online and wearing a self-tracking device?

Previous research showed that seeking health related information on the Internet was most common for young, women, and high education and income (Beaudoin & Hong, 2011; Anker et al, 2010). Against the literature surveyed, we expect certain demographic characteristics to influence technology adoption, such as age, education, income and gender adoption (Cotton & Gupta, 2004; Beaudoin & Hong, 2011). Moreover, regardless of the technology used, legacy socio-demographic factors influence the purpose of their usage (Neter & Brainin, 2014).

We investigate access to health information across two dimensions, one which retrieves information about other individuals with similar conditions (search online) and the other which retrieves information about oneself. By comparing these two activities, the study offers a better look at the processes and consequences of online health searches. The first instance, online search, can be undertaken with widespread technology, namely desktop computers, laptops or even mobile devices; while self-tracking devices require specialized watches, activity trackers, and sensors. We expect the usage of self-tracking devices to be influenced by age (young adults), education (higher level) and income as inferred from the literature on digital inequalities and usage (van Deursen & Van Dijk, 2014 a,b). Previous studies found that patients who travel longer times to receive care were more likely to use the Internet to access health information (Bundorf et al., 2006). Applied to the Finnish context, we expect to find individuals residing in the rural areas, farther away from health care centers, use the Internet for health-care information most.

Data and Methods

We used data collected by Statistics Finland between 2006 and 2016. The data were collected each spring and summer as part of the "ICT use by individuals and households" survey, which serves as the source for official Statistics for both Finland and the European Union. The data were collected through phone interviews and online surveys. Prior to 2014, the response rates for Statistics Finland's surveys were between 65-70 percent , but the 2016 survey gave a lower response rate of 53 percent. Respondents have been selected using random sampling from the national population register. Measurements included both standardized variables based on Eurostat's questionnaire on ICT usage as well as data derived from the population register, including age, gender, residence, education, and income. Statistics Finland's weight coefficients have been used to reduce the skewed effects of missing values, sample sizes, and individual characteristics (see OSF, 2016).

We used two variables as dependent measures in the analysis. *Health information search on the Internet* was measured by the question ”Have you used the Internet to search for information on diseases or health during the past three months?”. In more detail, this item measured on a dichotomous scale (“Yes” / “No”) whether the responded searched information on diseases, nutrition or health on the Internet for their private purposes (excluding work-related use purposes). *Self-tracking* was measured by the item “Have you used smart devices that measure movement during the past three months?”. This measurement included fitness trackers and smart watches that quantify movement, calories burned or sleep tracking. Again, the variable was measured on a dichotomous scale (“Yes” / “No”). Together, even though obviously coarse measures, these two items provided information on whether respondents used these technologies or not, but left unanswered questions regarding how often these technologies were used (frequencies) or why (purpose of usage).

Independent variables included age, education, gender, income, type of municipality. *Age* was divided into six age groups from 16-74: 16-24, 25-34, 35-44, 45-54, 55-64, 65-74 year olds. *Education* had three categories, namely “Primary”, “Secondary”, and “Higher degree”. *Gender* was coded as either ‘Man’ or ‘Woman’. *Income* was measured using quartiles, based on the respondent's stated net-income per month; cut-off points were below 1600 EUR, between 1600 and 2599 EUR, between 2 600 and 4099 EUR, and 4100 EUR and above. Lastly, the *type of municipality* divided respondents according to the geographic area in which they reside, namely “City”, “Suburban” and “Rural” municipalities. In Table 1, we summarize the descriptive statistics of both the dependent and independent variables.

<Table1 Descriptive statistics for all variables>

For our analysis, we used descriptive statistics and logistic regression models. The results of the logistic regression were reported using average marginal effects, as we compare differences in outcomes for searching health related information on the Internet and using a self-tracking device across the two models. Compared to odds ratios which are affected by unobserved heterogeneity in the independent variables, marginal effects account for all the observations in the sample (Mood, 2010). Analysis has been carried out with Stata 14.

Results

We answer our first research question using the logistic regression models (Tables 2 and 3). Below, we report the extent to which sociodemographic and economic determinants associate with searching for health information online or wearing a self-tracking device. We first examined the effects of age, education and gender in the first model, and income and municipality type in the second one. Finally, we entered all variables into the third model.

<Table 2 Average marginal effects for independent variables predicting health information search in 2016>

Note: Average marginal effects (AME), with reference category in Italics. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

M1: age, education, and gender effects; M2: income and municipality type effects; M3: all variables effect

Table 2 shows the probabilities of searching for health information online by independent variables. The data were fitted into three models. All socio-demographic variables appear to be significant in the first two models. Age had a negative effect on health information search, with those over 45 years old being between 12.9% and 18.3% less likely than early adults to undertake such activities. Respondents who hold secondary and higher degrees were respectively 8.9% and 17.9% more likely to search health information online than those with primary education. Our data also show that women were 15.4 % more likely to search information online than men. Income was a significant predictor only in the upper quartiles. Those in the 3rd quartile category were 8.9% more likely and those with incomes in the 4th quartile were 10% more likely to search health information online than the low income earners. There was also a significant effect of the municipality type respondents reside in. Compared to urban dwellers, suburban and rural inhabitants were 11.2 and 10.8 % respectively less likely to search for health information online.

In the third model, the municipality type effect disappears. Age, education, gender and income, however, remain significant predictors of searching for health-related information online. Age had a negative effect (between 15.8 and 19.7%), yet education had a positive effect: Secondary education holders were 7.6 % more likely to search health information online and higher educated individuals were 14.2% more likely than those with primary education. Women were 15.7% more likely to search health related information on the Internet than men. Compared to those in the 1^{st} quartile, 2^{nd}, 3^{rd} and 4^{th} quartile respondents were respectively 8.7, 9.7 and 11.8% more likely to search for health information online. The third model explained 12% of total variance, which showed that socio-demographic background variables selected in this model were reliable predictors of searching health information online.

<Table 3 Average marginal effects for independent variables predicting wearing a self-tracking device in 2016>

Note: Average marginal effects (AME), with reference category in Italics. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
M1: age, education, and gender effects; M2: income and municipality type effects; M3: all variables effect

Table 3 shows the probabilities of using a self-tracking device in different population groups. Again, we fitted the data into three models. In the first and second models, only age and income had significant effects. Age had a positive effect on the probability of using an self-tracking device, with the 35-44 year old's category being 7.9% more likely than 16-24 year olds to use such devices. In contrast, 65-74 year olds were 5% less likely than young people (aged 16-24) to use self-tracking devices. When investigating the effect of income, those in the 3^{rd} and 4^{th} quartile were 5.5% and 13.9% respectively more likely to use tracking devices than those in the first quartile. In the third logistic regression model, the effect of age disappears and the effect of income diminished to 3.9% and 10.4% respectively for the corresponding categories of the final model. The proportions accounted for are relatively modest with less than 10 % of total variation explained.

To answer our second research question, we analyzed the differences in demographic factors associating with searching for health information online and wearing a self-tracking device. We observed that the differences between Finns when searching for health information online follow 'established' patterns in the digital divide literature, according to age, education, gender, and income(Table 2, M3). In comparison, the adoption of new technological gadgets such as activity trackers and smart watches are largely influenced by income (Table 3, M3). This suggests that in Finland too, the digital divides are re-iterative and pervasive across different technological advancements.

Discussion

The present article investigates the usage of ICTs for health and wellbeing management. In detail, we analyze the factors that associate with health information search and self-tracking device usage. Our representative population-level study of Finns found that younger demographics, those with higher levels of education and income, women and inhabitants of big Finnish cities associate with seeking health information online. Moreover, when investigating the use of more recent technological advancement such as self-tracking devices measuring aspects of health and wellbeing, the only variable associated is income. This finding suggests that the factors leading to digital usage disparities are pervasive and associate with the cost of acquiring self-tracking devices. Previous research showed that seeking health related behaviour on the Internet was most common for young, women, and consumers with high education and income (Beaudoin & Hong, 2011; Anker et al, 2010). Our study aligns with such previous findings. In contrast to Buenaflor and Kim's (2013) factors, we did not find significant effects for age and gender that influence the use and acceptability of wearable devices; instead, we identified the effect of income. Additionally, we also found an association of the residence area, which has received little attention in the research on ICT usage.

The Internet has become a preferred resource for health related information even for individuals who primarily gain information from traditional media (books, magazines) or healthcare professionals (Jacobs et al., 2017). Studies have documented an increase in online tools and technologies available supporting health self-management (Bodenheimer et al., 2002; Alpay et al., 2011). In the specific case of health management, equally important are content skills required to sift through and make sense of the health information (Neter and Brainin, 2012) and digital skills to navigate the online environment. As Norman and Skinner (2006: 2) note, "[B]eing health literate in an electronic world requires a different or at least expanded set of skills to engage in health care and promotion". Our results show that only certain Finnish groups – young, well educated, mostly women of higher incomes living in cities – seek health-related resources online. By means of comparison, those who would mostly benefit of the Internet resources (because of the long distances to health-care centers in the Finnish countryside) actually seek health-information online the least. When it comes to self-tracking, the most salient factor becomes income, whether individuals possess enough disposable income to purchase a tracking device. In perspective, in 2016 when our data was gathered, wearables were worn by 12.2% of individuals in our sample (see Table 1). Such early adopters are tech-savvy and own good digital skills but are hardly representative of the entire population.

On the other hand, the ICT use for health management was found to have positive effects on clinical outcomes, including self-care and health related skills development as well as persuasive and motivating effects on health improvement (Portz et al., 2016). Andreassen (2012: 91) notes that "[P]atients use technology to increase flexibility and manage illness *in* everyday life, not only to 'gather knowledge *of* reality'" (italics in original). At the policy level, the European Commission claims that increasing numbers of individuals want to be actively involved in managing their health rather than relying solely on health professionals (Andreassen, 2012). Andreassen claims that 'patients' and 'health consumers' are intertwined in the EU e-health policy and that the policy does not distinguish between the two. However, the aforementioned positive effects and flexibilities are unevenly spread: digital divide scholars have long documented that 'new divides' based on skills and usage (Hargittai, 2002; Hargittai & Walejko, 2008; van Deursen & Van Dijk, 2014 a,b) rather than access to technology emerge.

The results of these studies need to be interpreted in the light of the following limitations. First, since health information can be classified as sensitive, future studies need to go beyond usage and consider privacy calculus, not only technology acceptance (Li et al., 2016). Second, we know that individuals retrieved health-related information but lack knowledge to which extent they contributed health-information themselves online. Third, we lack data on the source of health-information accessed and its reliability, namely whether it was contributed by health-care professionals or peers. Fourth, health information search is a very broad measure and it is impossible to determine whether the search is linked to the individual searching or family members. Finally, frequencies of health-related information are unknown; to which extent do individuals retrieve information online or from their tracking devices and how does it impact their health management decisions? These are questions we cannot explore with our dataset but hope that future research can look into.

Conclusion

Our study showed that despite the hype of universal access to the Internet, only certain demographics are able to use it to their health benefits. We investigated the case of online health information retrieval and use of a self-tracking device on a representative sample of the Finnish population. We found that disparities exist particularly among established factors of digital inequality, namely age and income were the most important predictors of online health information retrieval and use of a self-tracking devices. Our findings probably reflect consumers' personal hesitancy to utilize health-related information and new technologies. The existing divides among population groups tend to persist. We conclude with the argument that, the digital inequalities as they relate to seeking health information online and wearing self-tracking devices are explained by socio-demographic and economic factors. This period of technology introduction can persist for a relatively long time for certain population groups.

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Tables and Figures

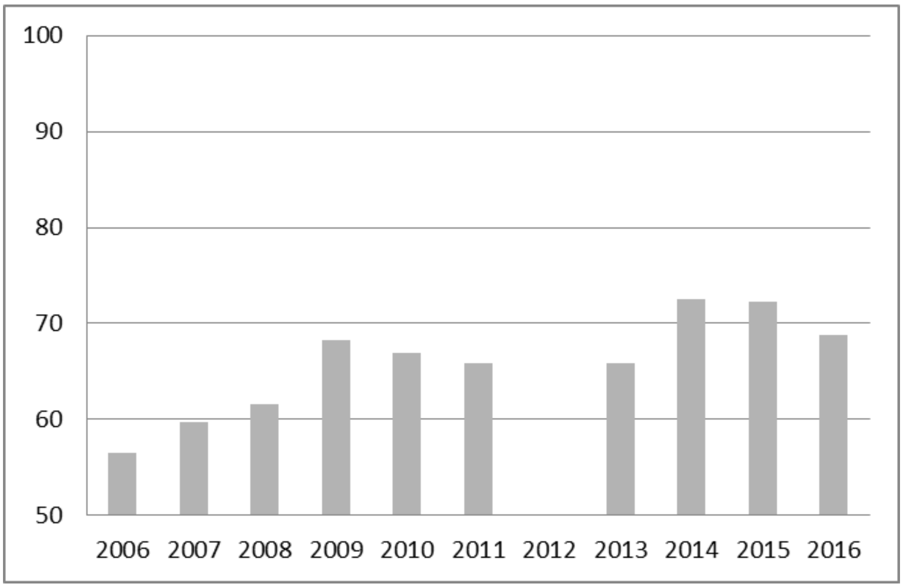

Figure 1 Health information search on the Internet, 2006-2016 (%). Source: OSF (2017)

Note: Data for 2012 not available.

Table1 Descriptive statistics for all variables

		N	%
Dependent variables			
Health information search N= 2498	No	779	31.2
	Yes	1719	68.8
Using a self-tracking device N= 2660	No	2337	87.8
	Yes	323	12.2
Independent variables			
Age N= 2661	16-24	370	13.9
	25-34	460	17.3
	35-44	439	16.5
	45-54	474	17.8
	55-64	488	18.3
	65-74	429	16.1
Education N= 2661	Primary	657	24.7
	Secondary	1157	43.5
	Higher degree	847	31.8
Gender N= 2661	Man	1328	49.9
	Woman	1333	50.1
Income N= 2469	1st quartile	445	18
	2nd quartile	538	21.8
	3rd quartile	790	32
	4th quartile	696	28.2
Municipality type N= 2661	Urban	1903	71.5
	Suburban	394	14.8
	Rural	364	13.7

Table 2 Average marginal effects for independent variables predicting health information search in 2016

		Health information search (M1)	Health information search (M 2)	Health information search (M3)
Age	*16-24*	(.)		(.)
	25-34	0.033 (0.036)		0.013 (0.036)
	35-44	-0.030 (0.039)		-0.061 (0.041)
	45-54	-0.129** (0.039)		-0.158*** (0.041)
	55-64	-0.183*** (0.037)		-0.197*** (0.039)
	65-74	-0.174*** (0.037)		-0.192*** (0.039)
Education	*Primary*	(.)		(.)
	Secondary	0.089** (0.034)		0.076* (0.035)
	Higher degree	0.179*** (0.034)		0.142*** (0.036)
Gender	Man	(.)		(.)
	Woman	0.154*** (0.021)		0.157*** (0.021)
Income	*1st quartile*		(.)	(.)
	2nd quartile		0.066 (0.038)	0.087* (0.040)
	3rd quartile		0.089** (0.034)	0.097** (0.037)
	4th quartile		0.10** (0.034)	0.118** (0.038)
Municipality type	*Urban*		(.)	(.)
	Suburban		-0.112*** (0.032)	-0.056 (0.031)
	Rural		-0.108** (0.034)	-0.062 (0.035)
Pseudo R^2		0.10	0.03	0.12

Note: Average marginal effects (AME), with reference category in Italics. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
M1: age, education, and gender; M2: income and municipality type; M3: all variables

Table 3 Average marginal effects for independent variables predicting wearing a self-tracking device in 2016

		Using a self-tracking device (M1)	Using a self-tracking device (M2)	Using a self-tracking device (M3)
Age	*16-24*	(.)		(.)
	25-34	0.039 (0.03)		0.041 (0.033)
	35-44	0.079* (0.034)		0.064 (0.036)
	45-54	0.052 (0.031)		0.030 (0.033)
	55-64	-0.010 (0.0257)		-0.021 (0.029)
	65-74	-0.050* (0.023)		-0.050 (0.027)
Education	*Primary*	(.)		(.)
	Secondary	-0.013 (0.021)		-0.018 (0.024)
	Higher degree	0.045 (0.025)		0.019 (0.027)
Gender	Man	(.)		(.)
	Woman	-0.002 (0.014)		0.010 (0.014)
Income	*1st quartile*		(.)	(.)
	2nd quartile		0.026 (0.020)	0.020 (0.021)
	3rd quartile		0.055** (0.019)	0.039* (0.020)
	4th quartile		0.139*** (0.022)	0.104*** (0.024)
Municipality type	*Urban*		(.)	(.)
	Suburban		0.002 (0.020)	0.015 (0.021)
	Rural		-0.008 (0.022)	0.002 (0.021)
Pseudo R^2		0.05	0.04	0.07

Note: Average marginal effects (AME), with reference category in Italics. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
M1: age, education, and gender; M2: income and municipality type; M3: all variables