1. Title: EXPLORING FACTORS IMPACTING SHARING HEALTH-TRACKING RECORDS
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3. This research has been funded in part by NSF under grant #____ (will provide # upon acceptance)
4. Key words: self-tracking, health-tracking, information sharing, health-motivation, health belief model
5. Running title: EXPLORING FACTORS IMPACTING SHARING HTR

Abstract

With the introduction of modern health technologies, the phenomenon of patients tracking health records has increased considerably in the recent past. The current study aims to examine the sharing of health-tracking records (HTR) by patients with different categories of acquaintances (spouse/partner, relatives, doctors, other). In this paper, we explore the critical factors that impact sharing of self-tracked information across two levels of sensitivity of HTR. Our study investigates how health motivation (HM), perceived health status (PHS), severity of health, and age influence sharing of self-tracked information. To do so, we adapted and applied the Health Belief Model (HBM) as a theoretical framework. The study employed multinomial logistic regression analysis to investigate the various factors that influence sharing of two types of HTR with different acquaintances. The statistical results were weighted to correct for known demographic discrepancies. Results indicated that HM, severity, and age substantially increase the likelihood of sharing HTR with health or medical professionals in comparison to other categories. In contrast, PHS increases the likelihood of information sharing with “other” acquaintances as opposed to with doctors. These findings are consistent with existing theory on HBM, wherein behavior appears to be predicted on the basis of/by both the individual’s motivation to achieve an outcome and the expectation that a specific action will result in that outcome.

Introduction

As one of the greatest Roman poets Publius Vergilius Maro (Virgil) wrote, “The greatest wealth is health.” Indeed, almost everyone cares about his or her own health. Modern health technologies, such as computer programs, websites and online tools, applications for mobile devices, and medical sensors, are motivating many of today’s consumers and patients to become even more active participants in their own care. According to a Pew Internet Health Study (1), 7 in 10 U.S. adults track at least one health indicator for themselves (e.g. weight, diet, exercise routine, blood sugar, sleep patterns, headaches, etc.). Of those adults, 34% share their health-tracking records (HTR) or notes with others, such as relatives or healthcare professionals. Yet, others prefer not to disclose sensitive health data, thus maintaining their privacy. Self-tracking of health indicators can be used for self-reflection to help people become more aware of their own behavior (2), make better decisions (3), and even affect health care behavior (4).

Keeping self-tracked health information often leads to concerns about exposure of these data (similar to concerns about personal health information in electronic medical record systems) and therefore, raises privacy concerns, especially if the information is recorded and stored electronically, locally, or in “the cloud.” Such concerns are also manifest when self-tracked information is stored offline. Risks stemming from exposure of such information include, but are not limited to, identity theft, personal image damage, and reputation damage. Even though health information tracking and sharing of records afford numerous benefits to consumers and patients, they could also increase the likelihood of unauthorized privacy disclosure, thereby producing negative consequences.

Sharing of HTR appears to blend the information-sharing phenomenon with the embedded component of information privacy. The sharing can occur either offline or online — not only can one verbally share sensitive information on self-tracked health indicators with acquaintances in personal communication, but also share such information using Internet tools, such as social media, health social networks, health-tracking services, blogs, etc., thus raising considerable concerns about privacy. Adapting the definition of Rafaeli and Raban (5), we define information sharing as the act of providing or contributing information (e.g. HTR) with the aim of receiving an answer or reply, in the form of words or through some action. A sizable body of literature deals with information sharing issues, but the issues of patient sharing of health tracking records remain largely unaddressed. This study focuses on the issues pertaining to sharing HTR of two different types with four categories of acquaintances. Particularly, it explores the critical factors that influence sharing of HTR by investigating how health motivation, perceived health status, severity, and age impact the sharing of one’s health indicators with spouse/partner, relatives, physician or healthcare professional, and other acquaintances. We use the Health Belief Model (6) as the theoretical basis for investigating the factors that impact sharing HTR with others—specifically, by adapting a model proposed by Becker et al. (7). Additionally, the study explores whether sharing HTR behavior might differ between individuals of different ages. The findings could be of value for scholars studying privacy in healthcare, engineers and software developers working in the field of self-tracking IT-artifacts, or policy makers addressing issues of online privacy. The research question can be summarized as follows:

RQ: What is the impact of health motivation, perceived health status, severity, and age on the likelihood of a patient sharing different types of HTR with their spouse/partner, relative, doctor, or other acquaintances?

The paper is organized as follows. The next section reviews the literature on information sharing, information privacy, and self-tracking. The paper subsequently discusses the research model, which is followed by an explication of the method used. After presentation of the results, the paper concludes with a discussion of those findings and their implications.

This research paper makes two significant contributions to the literature. First, it explores how health motivation impacts sharing of health-tracking records with different categories of acquaintances. Second, it adapts the Health Belief Model while applying that model to the context of sharing self-tracked health information. Additionally, the paper advances current knowledge on the issues pertaining to the concept of self-tracking by examining them from the perspectives of information sharing and information privacy.

Literature Review

Perspectives on Information Sharing and Privacy

Whereas information sharing has been widely addressed in various studies, sharing health-tracking records is a phenomenon of the recent past. Consequently, there is scarce information about this topic available in the literature. Importantly, HTR contains information that could be classified as sensitive or confidential, requiring special care and handling. To shed light on the sharing of HTR, we investigate it from two perspectives: one pertaining to information sharing, and another pertaining to information privacy. A study of 511 patients, (8) found that the majority (>90%) supported computerized sharing of health related information, yet fewer agreed that it should be shared outside of the health care circle (<70%) Another (qualitative) study of consumer attitudes showed that sharing psychological electronic records is beneficial for cancer patients, yet it also demonstrated that they felt strongly about the privacy and control over the information they provide (9). Additionally, another study on sharing health data between people with epilepsy on an online platform revealed a number of benefits, such as finding another patient experiencing the same symptoms, gaining a better understanding of seizures, and learning more about symptoms or treatments (10). In terms of the categories with whom people tend to share health related information, one study showed that 4 of 5 respondents were interested in sharing access to their personal health records with someone outside of their health system — a spouse, a child, or other family members (11). This notion found support in a recent

study of patients who share transparent visit notes with others, highlighting that more than half of the participants would like the option of letting family members or friends access their records (12). And also in a study of patients using mobile phone application, it was emphasized that a vast majority would allow their health records to be shared with family members, medical workers, and health care providers (13).

Sharing of information differs from posting information akin to a “broadcast” mode. That is, it depends on the kindness of peers, friends, or complete strangers or on some intangible reward structure. For the purposes of the current study, we define information sharing as the act of providing or contributing information with the aim of receiving an answer or reply. In the context of HTR sharing, this could be the contribution of self-tracked data to a database or dissemination of such data to another person with the aim of obtaining new knowledge (e.g., diet schedule, sleeping pattern adjustment, exercise regimen). Clearly, people do not participate equally in information-sharing activities. Furthermore, certain costs are associated with such sharing, such as investment of time and effort to share, and information privacy concerns. Thus some positive motivation is needed beyond the reduction of barriers to engage in sharing.

Information privacy is of growing concern to multiple stakeholders, including business leaders, privacy activists, scholars, government regulators, and individual consumers. For instance, poll results released by the Consumer Reports National Research Center reveal that most Americans are very concerned about what is being done with their personal information online (14). Among the most often cited contexts for privacy-related beliefs (15) are (a) the type of information collected from individuals (e.g., behavioral, financial, medical, biometric, consumer, and biographical) and (b) the use of information by different sectors (e.g., health care, marketing, and finance). The former is sometimes referred to as contextual sensitivity or information sensitivity (16). Information about lifestyle characteristics and shopping habits and preferences, for instance, is considered less sensitive than medical, and financial information (17).

A number of studies have explored privacy in the context of health care and information sharing (18),(19), (20), (21). They have established that respondents report a range of benefits from health information sharing. Yet, health related information is personal in nature and its sharing may involve privacy drawbacks (22). Thus, concerns for health information sharing raise questions about how to keep data private, what type of data to share, and with whom (23), (24).

Self-tracking

Several recent studies have addressed the concept of self-tracking in different contexts (25), (26), (27), (28). Li et al. (29) refer to *personal informatics*—defined as an activity where people collect and reflect on personal data to gain a better understanding of their own behavior and self-knowledge. According to these authors, people may use almost any tool for personal informatics purposes, ranging from computers and electronic devices to paper and even one’s own mind. Swan (30) posited, “In some sense everyone is already a self-tracker since many individuals measure something about themselves or have things measured about them regularly, and also because humans have innate curiosity, tinkering, and problem-solving capabilities.” Wolf and Kelly introduced the term *quantified self* (QS) as “a collaboration of users and toolmakers who share an interest in self-knowledge through self-tracking” (31). The primary methodology of self-quantification is data collection, followed by visualization, cross-referencing, and the discovery of correlations.

The concept of QS implies that an individual is engaged in the self-tracking of any kind of biological, physical, behavioral, or environmental information. Importantly, the individual takes a proactive stance toward obtaining information and acting on it. For example, an individual may measure his or her own weight or follow a certain diet to lose weight. Individuals can track a wide variety of areas—for example, energy level, mood, time usage, sleep quality, health indicators, cognitive performance, athletics, and learning strategies.

Swan (32) considers quantified self-tracking to be an emerging patient-driven health care model—that is, a type of service offered by some health social networks (e.g., TuDiabetes, PatientsLikeMe, CureTogether, MedHelp, SugarStats). The self-tracking functionality consists of easy-to-use data entry screens for conditions, symptoms, treatment and other biological information. The information can then be seen as a graphic display, possibly with data about the number of views by the individual, aggregated population, or custom groups. In the recent past, there appears to have been an increase in the use of self-tracking tools, particularly in the health and fitness sector, but these tools are also being used in the management of chronic diseases (33).

Health institutions are required to protect the privacy of these kinds of health data, but individuals are free to share their own data and post those data publicly. Many individuals might not be comfortable with sharing their self-tracking records, whereas others might be willing to contribute their data to create a valuable public good that is usable by all or to get rewarding reactions from other users.

Privacy Views on Sharing HTR

The ability to easily and inexpensively collect data about ourselves has its downsides and might pose certain privacy and confidentiality risks. Health-tracking records, financial records, or even the “friends” section on Facebook could all provide information about an individual that one might not be willing to share with others. In turn, people tend to keep certain parts of their data private from third parties, government, and even family members and friends. Unauthorized access to personal data or sharing of it with an unwanted entity might end in embarrassment, negative financial impact, or even pose danger to life. Disclosing precise data about ourselves, our personalities, and whereabouts makes us vulnerable. Imagine the possible negative consequences if, for example, colleagues find out about a delicate habit or disease of an individual; or if a swindler gains access to an individual’s sensitive information such as Social Security or bank account numbers; or if a criminal obtains one’s daily schedule and regular routes and locations.

According to the Privacy Rights Clearinghouse’s study (34) of mobile health and fitness applications, “from both a consumer and technical perspective, it is clear that there are considerable privacy risks for users—and that the privacy policies for those apps that have policies do not describe those risks.” Among the major findings of this technical risk assessment, which aimed to view the actual flow of personal information back to the app developer and to third parties, were the following: many apps send unencrypted data and connect to several third-party sites without user knowledge; unencrypted connections potentially expose sensitive and embarrassing data to everyone on a network; and 72% of the assessed apps presented medium (32%) to high (40%) risk regarding personal privacy. Another study on contextual expectations of privacy in self-generated health information flows also highlighted that despite respondents enjoying the benefits of tracking and sharing, they also care about the privacy of their health information flows, and they struggle to operationalize those preferences (35).

Currently, there is a gap in the literature addressing the issues of which specific factors might influence sharing HTR with different categories of acquaintances. Because motivation has been shown to affect information sharing, we examine the relationship between health motivation and sharing HTR. The present study also examines the impact of age on sharing HTR with different categories of acquaintances, an aspect that has not yet been explored in detail in literature to our knowledge.

Research Model

The dependent variable in our model is the sharing of health-tracking records, that is, “whom (which category of acquaintances) a respondent shares HTR with”. The main independent variables are health motivation, perceived health status, severity, and age; education is used as a control variable.

Constructs and Hypotheses

A number of conceptual models have been proposed to attempt an explanation of individual health-related behaviors. Most notable have been the frameworks advanced by Zola (36), Rosenstock (37), Andersen (38), and Becker et al. (39). Among these is the Health Belief Model (HBM), which has received the most direct attention (40), (41) and has influenced much additional research (6).

Considerable empirical support for HBM has been provided by studies of preventive health, illness, sick-role behaviors, and patient compliance (7), (39). The HBM model has been applied to issues as varied as individual health behavior (42), (43), users’ computer security behavior (44), and immigration intention (45). The present study evaluates HBM’s ability to explain and predict HTR sharing.

The HBM relates psychological theories of decision making to an individual’s decisions about alternative health behaviors (46). Rosenstock (6) attributed the origins of the behavior motivation theory underlying the HBM to the Lewinian theory of goal-setting in the level-of-aspiration situation. Lewin et al. (47) hypothesized that behavior depends on two variables: (1) the value placed by an individual on a particular outcome and (2) the individual’s estimate of the likelihood that a given action will result in that outcome. The following health-related correspondences have been postulated by Becker et al. (7): (1) motivation to avoid certain health condition or to get well; (2) amount of desire for a particular level of health; and (3) belief that a specific health action will positively impact a certain health condition.

Health motivation, defined as one’s goal-directed arousal to engage in certain health-related behaviors (48), (49), (50), is examined in the present study as a main predictor. This characteristic focuses on the interest and willingness of individuals in performing health-related behaviors (51), (52).

We adapted Becker et al.'s (7) model for predicting and explaining health-related behaviors; using the health motivation construct as a predictor and included both willingness to seek medical diagnosis/direction and positive health activities. Table 1 in Appendix A describes the instruments pertaining to each construct used in the current study.

Research examining health motivation has found it to be associated with most health-related behaviors. Likewise, Becker et al. (7) posited that positive health motivations exist. Similarly, we propose that health motivation increases the likelihood of HTR sharing. Our rationale is that health motivation's arousal should drive individuals to engage in activities such as HTR sharing that would provide them with helpful, supportive, and dependable information received from trustworthy individuals, such as health or medical professionals. We hypothesize:

Hypothesis 1: Health-motivated individuals will be more likely to share HTR with health or medical professionals vs. other categories of acquaintances.

Perceived health status is viewed as a resource that indicates subjectively measured individuals' mental and physical abilities to select and implement health behaviors (50). It conceptualizes good health as an ability, and suggests that individuals can utilize their current health as a resource to assist them in engaging in additional health-related behaviors. Research shows that this construct has a positive impact on cancer detection behavior (53) and health/illness information seeking (54), but a negative impact on health counseling in a hospital (55). In the context of HTR, perceived health status might potentially affect individuals' willingness to share HTR. On the one hand, individuals with apparently better health might be unwilling to share health-related information with health professionals considering it an intrusion into their privacy. On the other hand, people with poorer perceived health might share their records so as to receive feedback or support related to a disease or condition from medical professionals. Thus, we suggest that individuals with higher perceived health status are less health motivated and will be less likely to share HTR with doctors and other medical professionals. Thus we hypothesize:

Hypothesis 2: Individuals with a higher perceived health status will be less likely to share HTR with health or medical professionals.

In this paper, we consider *factual* severity and refer to it as the degree to which an individual lives with any serious health problems or conditions (higher number is associated with higher severity). This dimension includes both medical/clinical consequences (e.g., death, disability, pain) and social consequences (e.g., effects on work, family life, social relations) (56).

The HBM suggests that health-related action depends not only on the belief that one is susceptible to a serious health problem but also on how one perceives its severity. As a major component of the HBM (39), (57) severity seems to capture a critical part of what is on people's minds when they are faced with the fact of encountering multiple serious health problems. The HBM proposes that when individuals see a threatening disease and realize how they can benefit by taking preventive action, they are likely to take action. In other words, if the perceived benefits of taking certain actions to deal with an encountered disease are viewed as greater than the perceived threats posed by the disease, individuals are likely to modify or engage in health-related behaviors.

Earlier health studies reported that individuals with severe mental health conditions (or those who care for such people) were often reluctant to release their health-related information (19). However, a recent study of patients' sharing psychological information within the multidisciplinary cancer care team reported an array of perceived benefits (9) similar to those reported by populations with other diseases. Hence, we suggest that individuals who live with more health problems or serious conditions are more likely to take action and engage in sharing their HTR with health or medical professionals. Thus we hypothesize:

Hypothesis 3: Individuals with higher severity will be more likely to share HTR with health or medical professionals vs. other categories of acquaintances.

Age reflects individuals' mental and physical ability to engage in health-related behaviors. Increased age is often associated with less ability. Age inhibits health information acquisition because of the declining cognitive and perceptual skills of the elderly individuals (58), (59). In the context of privacy context, those consumers who are less likely to be concerned about privacy are more likely to be young (60). A younger audience might, therefore have more likelihood than older adults to share HTR with certain categories of acquaintances; in contrast, older adults will be more interested to share with health professionals who can contribute to their health information acquisition. Zulman et al. (11) have also reported the finding that older adults express marginally more interest in sharing health related information than younger and middle-aged adults – we therefore hypothesize:

Hypothesis 4: Older individuals will be more likely to share HTR with health or medical professionals vs. other categories of acquaintances.

Education levels reflect an expertise that assists in health information processing and in selecting healthy behaviors (52). This factor has a positive impact on preventive health behaviors (55) and a negative impact on over-eating and smoking (61). Because higher education level has been found to encourage most types of health infor-

mation acquisition and health maintenance behaviors, we assume that in the context of HTR it could possibly promote or hinder information sharing and, therefore should be controlled.

Figure 1 summarizes the research model used in this study (value in parentheses specifies the comparison category).

(Insert Figure 1)

Methods

Sample

In our research, we analyzed survey data collected by Pew Internet & American Life Project between August 7 and September 6, 2012. The results reported here come from a survey performed by Princeton Survey Research Associates International (62) of 3,014 adults living in the United States. Telephone interviews were conducted by landline (1,808) and cell phone (1,206, including 624 respondents without a landline phone), both geographically disproportionate. A combination of landline and cell random digit dial samples was used to reach a representative sample of all adults in the United States who have access to either a landline or a cellular telephone. Both samples were disproportionately stratified to increase the incidence of African-American and Hispanic respondents. Within strata, phone numbers were drawn with equal probabilities and as many as 7 attempts were made to contact every sampled telephone number. The Sample was released for interviewing in replicates, which are representative subsamples of the larger sample. Using replicates to control the release of the sample ensures that complete call procedures are followed for the entire sample. Calls were staggered over times of day and days of the week to maximize the chance of making contact with potential respondents. Each phone number received at least one daytime call. To adjust for effects of the sample design and to compensate for patterns of nonresponse that might bias results, weighting was accomplished in multiple stages to account for the disproportionately stratified sample, the overlapping landline and cell sample frames, and differential non-response associated with sample demographics.

Our research focuses on those individuals who indicated that they (a) had shared their HTR either online or offline, and (b) kept track of their own health related indicators. The total sample size was $N = 761$ cases, of whom 86.7% tracked own weight, diet, or exercise routine (HTR Type 1); and 59.4% tracked own blood pressure, blood

sugar, sleep patterns, headaches, or any other indicator (HTR Type 2). In terms of sharing these HTR, 20.7% shared HTR with their spouse, 25% with relatives, 46.5% with health or medical professional, and 7.7% with other acquaintances. Of the respondents, 38% were females; 74.5% were White, 16.6% Black, and 8.9% were from other races. The mean age of the participants in the sample was 54 y.o. ($SD = 19$), min 18, max 95. Evidently, the mean age of those who track HTR Type 2 was almost 10 years older than those who do not track these indicators (49 and 58 years, respectively, $d=0.47$ (medium)). Also, of the participants 38.9% lived with no health problems or conditions, 29% lived with one such condition, and the rest had 2 or more health problems or conditions. Further, among the participants 7% did not graduate from high school, 25% graduated, 19% had no college degree, 9% had 2-year associate degree, and 22% had 4-year college or university degree.

Measures

Sharing HTR. Since we focus only on those who share health-tracking records with others, our dependent variable refers specifically to those with whom a respondent shares HTR. The original variable encountered 10 categories (Table 1 in Appendix A), which we categorized into 4 groups based on frequency of responses — (1) spouse/partner (21%), (2) relatives (i.e. parent (5%), brother/sister/sibling (4%), child (7%), other family member (9%), 25% total), (3) health or medical professional (46%), and (4) other acquaintances (i.e. church or community member (1%), friend (4%), personal trainer or health coach (1%), other (3%), 9% total). Importantly, the respondents were given up to 3 mentions, so that there could be more than one category they share HTR with. However, second and third mentions encountered 85% and 98% of missing values, respectively, and were eliminated from further analysis. “Health or medical professional” category was chosen as a reference groups (base outcome) for further analysis.

Health Motivation (HM). Three binary items originally represented this latent construct. It captured whether tracking a certain health indicator affected one’s *own* health care routine or the way one cared for *someone else*. The latter portion of the responses was omitted in our analysis since we focused on ego-directed behaviors only. We employed factor analysis to analyze the shared variance between the items and to reduce the dimensions (63). To address the notion of factoring binary items we employed a two-step procedure (64) involving: (a) conducting tetrachoric correlation analysis (i.e. special case of polychoric correlation applicable when variables are dichotomous), and (b) running factor analysis of a tetrachoric correlation matrix. Additionally, we examined: (1) Kaiser-

Meyer-Olkin measure of sampling adequacy resulting in overall satisfactory value of 0.67, which is above the 0.5 threshold (65); (2) internal consistency using Cronbach's α resulting in a satisfactory for exploratory study coefficient of 0.63; and (3) the factor loadings (0.77, 0.7, and 0.64) considered “very good” above 0.63 and “excellent” above the 0.7 cut-offs (66). Single factor with eigenvalue of 1.5 was retained for further analysis.

Perceived Health Status (PHS). This ordinal variable captures the extent to which respondents subjectively rated their own health. The values ranged from 1 (poor) to 4 (excellent). The variable was treated as a scale assuming there are equal “distances” between the categories (i.e. the distance between “poor” and “fair” is the same as between “fair” and “good” and between “good” and “excellent”) (67). Additionally, we computed predicted values for two approaches (i.e. treating PHS as a scale and also as being dichotomized into 3 variables) and examined the correlations between the predicted values. Both were strongly correlated (above 0.82) indicating consistency of the predictions and supporting the notion of using PHS as continuous variable (68).

Severity. Originally represented by six binary items, this variable reflected whether a respondent was living with any of the following conditions: diabetes, high blood pressure, asthma, heart disease, cancer, other. To examine each respondent's number of health problems or conditions (assumed as proxy of severity), we summed the responses resulting in a scale variable ranging from 0 to 6. To check for potential bias of this approach, we conducted an examination of the correlations between the predicted values for two approaches (i.e. treating severity as a scale and also as dichotomized into 5 variables) and found strong correlation (above 0.8) indicating consistency of the predictions and supporting the notion of using severity as a continuous variable (68).

Education Level. Education level was a measure of the respondents' highest grade completed in school. The values ranged from 1 (none or grades 1–8) to 7 (postgraduate training/professional school after college). Education level was used as a control variable in our model and treated as a scale.

All cases where the response to the variable was “don't know” or “refused” were set as missing values.

Common method bias (CMB) may affect the estimates of the relationship between constructs if all data are self-reported and collected through the same questionnaire during the same period of time. To assess CMB, we employed Harman's single-factor test measurement (69). Confirmatory factor analysis (unrotated) was conducted to determine the number of factors needed to account for the variance in the variables. Neither a single factor emerged from the factor analysis (eigenvalues <1), nor did one general factor account for the majority of the covariance among the variables. The results indicated that common method variance was not a serious issue in our study.

We also carried out the marker-variable analysis suggested by Lindell and Whitney (70). Gender was employed as a theoretically unrelated variable to adjust the correlations among the principal variables. The results showed no high correlations between the marker and the principal variables (Table 1). Thus we concluded that common method bias was not a serious concern.

(Insert Table 1 here)

Method

We employed multinomial logistic regression (MLR) analysis using STATA 13 to investigate the factors influencing sharing HTR. MLR rests on two primary assumptions: (a) lack of multicollinearity, and (b) independence of irrelevant alternatives (IIA) (71).

To check for multicollinearity, we examined the correlations between the independent variables (Table 1). A significant moderate negative correlation was observed between perceived health status (PHS) and severity. However, since VIF analysis indicated the magnitude of collinearity to be 1.3 falling within the conservative threshold of 2.5 (72), we assumed no multicollinearity was present.

We performed the IIA assumption test using Stata's -mlogtest- for multinomial logit model (combines both Hausman and Small-Hsiao tests), which did not reject null hypothesis that odds are independent of other alternatives ($\chi^2 < p$, for all k-1 categories of the dependent variable).

Statistical results were weighted using standardized sampling weight (included in the data set by Pew Internet & American Life Project) to correct known demographic discrepancies. The survey's margin of error is the largest 95% confidence interval for any estimated proportion based on the total sample — the one around 50%. For example, the margin of error for the entire sample is ± 2.4 percentage points. This means that in 95 out of every 100 samples drawn using the same methodology, estimated proportions based on the entire sample will be no more than 2.4 percentage points away from their true values in the population.

Lastly, to examine the differential impact of the predictors, we examined the proposed model across two groups of respondents: (a) those who “currently keep track of own weight, diet, or exercise routine” (HTR Type 1 - Group 1); and (b) those who “happen to track own blood pressure, blood sugar, sleep patterns, headaches, or any other indicator” (HTR Type 2 - Group 2) (Appendix A, Table 1). The resulting sample sizes for the two groups were

n(1)=611 and n(2)=408, respectively. To further compare the (significant) coefficients between the groups, we calculated Wald chi-square statistics with 1d.f for each statistic (73).

Results

Table 2 presents the multinomial logistic regression results for groups 1 and 2 with response category 3 (i.e. health or medical professionals) set as a reference group (base outcome).

(Insert Table 2)

Hypothesis 1 predicted that health-motivated individuals would be more likely to share HTR with health or medical professionals vs. other categories of acquaintances. In case of group 1, this hypothesis was supported for all three comparisons (i.e.(1) spouse/partner, (2) relatives, and (4) other acquaintances vs. health or medical professionals (“doctors”) (3)). The results indicated that health motivated individuals are less likely to share HTR with acquaintances, but rather share them with doctors ((1-3) $\beta = -1.08$, $z = -2.89$, $p < 0.01$; (2-3) $\beta = -0.73$, $z = -1.98$, $p < 0.05$; (4-3) $\beta = -1.71$, $z = -3.37$, $p < 0.01$). If an individual were to increase the HM score by one point, the multinomial log-odds for sharing HTR with categories 1, 2, and 4 relative to doctors would be expected to decrease by 1.08, 0.73, and 1.71 units, respectively, while holding all other variables in the model constant¹. Interpreting these results in terms of relative risk ratios (RRR) we found that given a one unit increase in HM, the relative risk of sharing HTR with other acquaintances relative to doctors would be expected to decrease by factors of 0.34, 0.48, and 0.18 for groups 1, 2, 4, respectively, given that the other variables in the model are held constant. More generally, if individuals were to increase their HM, they would be expected to share HTR with doctors as compared to other categories. Additionally, the RRR for group 4 (i.e. “other acquaintances”) is significantly different compared to that for groups 1 and 2 ((1-3) $\chi^2 = 8.36$, $p < 0.01$; (2-3) $\chi^2 = 3.93$, $p < 0.05$). In case of group 2, hypothesis 1 was not supported, since all estimated HM coefficients are insignificant.

Hypothesis 2 predicted that individuals with a higher PHS will be less likely to share HTR with health or medical professionals. This hypothesis found support in case of both groups for the comparison between “other acquaintances” (i.e. category 4) and doctors. The results indicated that individuals with higher PHS are more likely to share HTR with “other acquaintances” (e.g. community member, friend, or personal trainer) than with doctors

¹ Referred further to as “*ceteris paribus*”.

((Group 1) $\beta = 0.68$, $z = 2.05$, $p < 0.05$; (Group 2) $\beta = 1.23$, $z = 2.01$, $p < 0.05$). If an individual's PHS were to increase by one point, the multinomial log-odds for sharing HTR with "other acquaintances" relative to doctors would be expected to increase by 0.68 and 1.23 units, respectively, *ceteris paribus*. In terms of RRR, given a one unit increase in PHS, the relative risk of sharing HTR with "other acquaintances" relative to doctors would be expected to increase by factors of 1.97 and 3.41 for groups 1 and 2, respectively, *ceteris paribus*. Generally, if individuals were to increase their PHS, they would be more expected to share HTR with "other acquaintances" as compared to doctors. Additionally, the MLR coefficients for PHS are not significantly different between the two groups ($\chi^2 = 0.63$, $\chi^2 < p$). Hypothesis 2 did not find support at other comparison levels for either of the groups.

Hypothesis 3 predicted that Individuals with higher degree of severity would be more likely to share HTR with health or medical professionals vs. other categories of acquaintances. This hypothesis was supported in case of group 1 for the comparison between categories 1 and 3 (i.e. spouse/partner vs. doctors). The result indicated that individuals with higher severity are more likely to share HTR with doctors relative to their spouse or partner ($\beta = -0.31$, $z = 2.01$, $p < 0.05$). If the individual's degree of severity were to increase by one point, the multinomial log-odds for sharing HTR with doctors relative to spouse/partner would be expected to decrease by 0.31 units, *ceteris paribus*. In terms of RRR, given a one-unit increase in severity, the relative risk of sharing HTR with doctors would be expected to decrease by a factor of 0.73. Thus, individuals with higher degree of severity would be more expected to share HTR with their doctors as compared to their spouse or partner. No significant support was found for the hypothesis at other comparison levels for either of the groups.

Hypothesis 4 predicted that older individuals will be more likely to share HTR with health or medical professionals vs. other categories of acquaintances. In case of group 1, hypothesis was supported for comparisons between categories 2 and 3, and 4 and 3 (i.e. relatives vs. doctors, and "other" vs. doctors, respectively). The results indicated that older individuals were more likely to share HTR with doctors relative to both categories 1 and 4 ((2-3) $\beta = -0.017$, $z = -2.2$, $p < 0.05$; (4-3) $\beta = -0.043$, $z = -3.24$, $p < 0.01$). If the age of the individual's were to increase by one year, the multinomial log-odds for sharing HTR with either relatives or "other acquaintances" relative to doctors would be expected to decrease by 0.017 and 0.043 units, respectively, *ceteris paribus*. In terms of RRR, given a one-year increase in age, the relative risk of sharing HTR with corresponding categories relative to doctors would be expected to decrease by factors of 0.98 and 0.95, respectively, *ceteris paribus*. In case of group 2, the hypothesis was supported for the comparison between "other acquaintances" and doctors. This result is consistent with that for

group 1 ((4-3) $\beta = -0.07$, $z = -3.33$, $p < 0.01$, $RRR=0.93$), yet the difference between the coefficients of the two groups is insignificant ($\chi^2 = 1.28$, $\chi^2 < p$). Generally, older individuals in both groups would be more likely expected to share HTR with doctors as compared to either relatives or “other acquaintances”.

To facilitate further discussion, we estimated the predicted probabilities for each outcome category separately (relative to base) and graphed two-way median-spline plots in support of hypotheses 1-4 for each significant predictor (Figure 2).

(Insert Figure 2)

Discussion

The empirical results of the study shed light on why people of different ages share their health-tracking records with different categories of acquaintances.

First, consistent with the theoretical model by Becker et al. (7) and a number of other studies (74), (75), HM has a significantly positive impact on health-related behavior. In particular, health motivation, created, for instance, by changing one's overall approach to overall health, by asking more questions, or by getting a second opinion, substantially increases the likelihood of sharing HTR (Type 1) with health or medical professionals relative to other categories of acquaintances. Sharing of HTR inside the health care circle in this case does not impose any privacy-related barriers and could serve to communicate positive experiences or achievements, or simply motivate one to be more engaged in own health-related behaviors. Interestingly, according to Figure 2, whereas the probability of sharing HTR with a spouse or partner decreases linearly, they are somewhat different in case of sharing HTR with relatives and “other acquaintances” — there are “spikes” of increased probabilities for sharing HTR with these categories when HM is approaching medium. This is especially visible in case of “other acquaintances”. It could be that patients are likely to ask others instead of doctors for second opinions at certain stages of their motivation-related actions.

Second, although not significant for comparisons between categories 1-3 and 2-3, PHS is significantly positively related to sharing HTR of both types with “other acquaintances” relative to doctors. Individuals with better health appear to be less health motivated and, therefore, engage less in sharing HTR with health or medical professionals. Rather, they are inclined to share them with others (e.g. community members, friends, personal trainer, etc.).

In this case, the notion of privacy as it relates to sensitive health data, does not seem to pose a barrier to sharing information with categories of acquaintances other than doctors or relatives. In contrast, individuals with fair or poor health conditions are less likely to share sensitive health data as part of seeking health-related information on treatment or preventive measures, available medical services, or emotional support with “other acquaintances”. Additionally, as shown on Figure 2, the probability of sharing increases for the Type 1 health-tracking records, suggesting a differential impact depending on the level of sensitivity of HTR. The variance of preferences of sharing HTR depending on their type is consistent with prior literature findings suggesting higher perceived risk associated with sharing more sensitive health data (11), (22).

Third, severity seems to play a role in impacting the likelihood of sharing HTR with spouse/partner relative to doctors. As Figure 2 shows, it is likely for individuals with 0 or 1 health problems to share their HTR (Type 1) with a close person, such as a spouse or a partner. Yet, with an increase in the severity of one’s health, they are turning to sharing HTR with health or medical professionals for dependable and trustworthy feedback. The fact that one’s health condition is severe (that is one lives with multiple health problems) leads them to disregard privacy-related concerns and share sensitive health data so as to decrease their chances of negative social or medical consequences such as the effects on the condition on their work, family life, pain, or even death.

Fourth, age appears to be a negative significant factor influencing sharing HTR. As indicated in Figure 2, (a) whereas the steepness of the decline in probability of sharing HTR (Type 1) with relatives in relation to doctors is minor (with “breaking points” at ages 40 and 60), it is substantial (for Types 1, 2) with “other acquaintances” relative to doctors. Not surprisingly, people tend to trust their beloved ones throughout life, whereas that trust declines abruptly with acquaintances, who may come and go. Furthermore, clearly older individuals tend to share HTR with health or medical professionals. In particular, the probability of sharing HTR with doctors is highest (lowest for “other acquaintances) for senior individuals, those above age 55-60, indicating apparent preference of sharing data on health indicators inside the health care circle. Moreover, from the standpoint of privacy seniors are least likely to share more personal (sensitive) health indicators (e.g. blood pressure, blood sugar, sleep patterns, headaches) with anyone but their doctors.

Additionally, we examined the age vs. severity and HM plot (Figure 3). Expectedly, the factual severity is positively related to age with gradual increases at 40 and (almost) 60 years old. Yet, HM remains rather steady across ages with upheavals from 25-40 and 55-75 y.o. suggesting the individuals’ desire to mitigate negative health

conditions or their consequences. HM then drops abruptly after 75 y.o. proposing future considerations aimed at supporting the elderly accordingly.

(Insert Figure 3)

The current study has useful theoretical implications for those conducting research in the newly emergent field of health self-tracking as well as for those exploring behaviors pertaining to sharing sensitive information suggesting that despite the considerable extent of embeddedness of privacy component in health related personal data, people are willing to share it for the perceived benefits associated with taking certain health-related actions. Importantly, the elucidation of the impact of age on sharing HTR with different categories of acquaintances by senior citizens provides new insights into the importance of their life partners and also doctors as critical sources of emotional and informational support. Additionally, we demonstrated that the HMB could be adapted and applied to the context of sharing self-tracked health information.

Conclusions

As is evident from the study the sharing of HTR appears to blend information sharing with the embedded component of information privacy. By adapting the HBM, our study demonstrated that the four factors (HM, PHS, severity, and age) influence the likelihood of health-related actions. As discussed above, the findings with respect to the four categories of acquaintance were consistent with existing theory on HBM. Furthermore, we advanced current knowledge on the issues pertaining to self-tracking by examining this context from the perspectives of information sharing and information privacy.

In terms of this study's public policy implications, we suggest that governments explore whether sharing HTR might be made easier for all citizens, yet preserving individuals' privacy at high level, and incentivize them to engage in it actively for the benefits of informational, emotional, or social support. Perhaps encouragement and education can be provided, with the caveat that those who share information using the Internet should protect their identities and not be vulnerable to web-trackers. Also, interventions (counseling) should be provided to those above the age of 70-75 aimed at increasing their health motivation in an attempt to cope with growing health problems or conditions.

This study has a number of limitations, which might guide further research. Because of the limitations inherent in our data set, we could not examine the impact of HM for people who have real health problems and for people who simply follow a healthy lifestyle. Additionally, for the same reason, we were not able to capture the level of detail at which HTR were shared. Furthermore, the severity of specific health conditions might have differential impacts on sharing HTR. For example, someone living with cancer and diabetes might differ in terms of sharing HTR behavior from someone with mental or physical disabilities. Also, because of the various barriers to sharing HTR, it would be worth exploring the online and offline cases separately. Such variables as privacy awareness and means of sharing HTR could possibly be barriers to this behavior and, therefore, should be considered in future studies. Lastly, future researchers are encouraged to consider other categories with which people can share (sell) their HTR for the purpose of financial gain.

Acknowledgments

This research has been funded in part by NSF under grant #0916612. The usual disclaimer applies. We thank the Editorial review board for critical comments that have greatly improved the paper.

Competing interests: None declared

Ethical approval: Not required

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Appendix A.

(Insert Appendix A Table 1)

Figure 1

Figure 1. Research model (comparison group in parenthesis)

Figure 2

Figure 2. Median-spline plots of predicted probabilities (Pr)

Figure 3

Figure 3. Age vs. Severity and HM

Table 1

Table 1. Correlations (Polychoric correlations are given in italics)

N	Variable	1	2	3	4	5	6	VIF
1	PHS	1						1.3
2	Severity	-0.51*** <i>-0.58***</i>	1					1.6
3	HM	-0.12** <i>-0.14**</i>	0.22*** <i>0.25***</i>	1				1.0
4	Age	-0.19*** <i>-0.21***</i>	0.39*** <i>0.46***</i>	-0.03 <i>-0.04</i>	1.0			1.2
5	Education (control)	0.15*** <i>0.17***</i>	-0.14*** <i>-0.14***</i>	0.009 <i>0.008</i>	0.0023 <i>0.003</i>	1.0		1.0
6	Gender (marker)	-0.07* <i>-0.1*</i>	0.07* <i>0.1*</i>	-0.002 <i>-0.0001</i>	0.08** <i>0.1**</i>	-0.07 <i>-0.08</i>	1	-

Table 2

Table 2. Multinomial Logistic Regression Results

DV (category)	IVs	Group 1 (Type 1 HTR)			Group 2 (Type 2 HTR)		
		Coef	SE	RRR	Coef	SE	RRR
1	Education	-0.06	0.06	0.94	-0.05	0.09	0.95
	Age	-0.008	0.008	0.99	0.009	0.009	1.01
	PHS	0.12	0.2	1.12	-0.05	0.22	0.95
	Severity	-0.31*	0.15	0.73	-0.35#	0.19	0.7
	HM	-1.08**	0.37	0.34	-0.79#	0.47	0.45
2	Education	-0.19**	0.07	0.83	-0.35***	0.09	0.7
	Age	-0.017*	0.007	0.98	-0.02#	0.01	0.98
	PHS	0.02	0.23	1.02	-0.27	0.25	0.77
	Severity	-0.2	0.16	0.82	-0.11	0.18	0.89
	HM	-0.73*	0.37	0.48	-0.27	0.46	0.76
4	Education	-0.14	0.09	0.87	-0.03	0.15	0.97
	Age	-0.043**	0.013	0.95	-0.07**	0.02	0.93
	PHS	0.68*	0.33	1.97	1.23*	0.61	3.41
	Severity	-0.53#	0.29	0.59	0.23	0.3	1.25
	HM	-1.71**	0.51	0.18	-1.29#	0.75	0.27
3	<i>Base outcome (comparison group)</i>						
Log likelihood		-659.8			-345.1		

#p<0.1; *p<0.05; **p<0.01 ***p<0.001

Appendix A

Table 1. Operationalization of the variables

Construct	Survey question	Question	Original Coding	Final Coding
Sharing HTR (categorical)	Q29	Whom do you share this information [HTR] with?		
		1. Respondent’s spouse/partner	0 = no, 1 = yes	1 = spouse/partner
		2. Respondent’s parent		2 = relatives
		3. Respondent’s brother/sister/sibling		
		4. Respondent’s child		
		5. Other Family member/Family relationship		3 = doctors
		6. Health or medical professional (includes doctor, nurse, therapist, physician’s assistant)		4 = “other acquaintances”
		7. Member of Group: Church, community association, volunteer group		
		8. Friend		
		9. Personal trainer or health coach		
		10. Other		
Health Motivation	Q30	In which of the following ways, if any, has tracking this health indicator affected your <u>own</u> health care routine [or the way you care for someone else]? Responses in brackets were omitted in the analysis.		
		a. Affected a decision about how to treat an illness or condition	0 = no, 1 = yes	Factor score, based on tetrachoric correlation matrix
		b. Changed your overall approach to maintaining your health or the health of someone you help take care of		
		c. Led you to ask a doctor new questions, or to get a second opinion from another doctor		
Severity	Q3	Are you now living with any of the following health problems or conditions?		
		a. Diabetes or sugar diabetes	0 = no, 1 = yes	Summed up to capture the degree of (factual) severity
		b. High blood pressure		
		c. Asthma, bronchitis, emphysema, or other lung conditions		
		d. Heart disease, heart failure, or heart attack		
		e. Cancer		

Construct	Survey question	Question	Original Coding	Final Coding
		f. Any other chronic health problem or condition		
Perceived Health Status	Q2	In general, how would you rate your own health — excellent, good, only fair, or poor?	1= excellent; 2=good; 3=only fair; 4=poor	Reverse coded
Education	Educ2	What is the highest level of school you have completed or the highest degree you have received?		
		1. Less than high school (Grades 1-8 or no formal schooling)	1 through 8	Kept original, assuming there are equal “distances” between the categories
		2. High school incomplete (Grades 9-11 or Grade 12 with NO diploma)		
		3. High school graduate (Grade 12 with diploma or GED certificate)		
		4. Some college, no degree (includes community college)		
		5. Two year associate degree from a college or university		
		6. Four year college or university degree/Bachelor’s degree (e.g., BS, BA, AB)		
		7. Some postgraduate or professional schooling, no postgraduate degree		
		8. Postgraduate or professional degree, including master’s, doctorate, medical or law degree (e.g., MA, MS, PhD, MD, JD)		
HTR Type 1	Q24	Now thinking about your health overall... Do you currently keep track of your own weight, diet, or exercise routine, or is this not something you currently do?	0 = no, 1 = yes	Considered Q24=1 as Group 1 in the analysis
HTR Type 2	Q25	How about any other health indicators or symptoms? Do you happen to track your own blood pressure, blood sugar, sleep patterns, headaches, or any other indicator , or any other indicator?	0 = no, 1 = yes	Considered Q25=1 as Group 2 in the analysis