Quantifying the Quantified Self: A Study on the Motivation of Patients to Track Their Own Health

Completed Research Paper

Henner Gimpel **Marcia Nißen**
Karlsruhe Institute of Technology (KIT)
Institute of Information Systems and Marketing
Englerstr. 14, 76131 Karlsruhe, Germany
henner.gimpel@kit.edu marcia.nissen@student.kit.edu

Roland A. Görlitz
FZI Research Center for Information Technology
Haid-und-Neu-Str. 10-14, 76131 Karlsruhe, Germany
goerlitz@fzi.de

Abstract

A new generation of patient-driven healthcare information systems (HIS) is emerging to advance traditional healthcare services and empower patient self-responsibility. Professional approaches to develop or improve HIS exist alongside evolving individual and community-shared approaches where patients take responsibility for their health data and health. Health Social Networks and the Quantified Self community are examples for such patient-driven initiatives. They inherently focus on empowering self-determination and responsibility. The success of future HIS relies – at least partially – on their engineers' and developers' capability to understand and use impulses from their respective target groups. The present study on self-tracking motivations aims to shed light on what drives people to track themselves. To this end, we conducted an exploratory survey with 150 self-trackers and developed a Five-Factor-Framework of Self-Tracking Motivations. The framework includes an inventory of five factors and a psychometrical scale of 19 items to measure individual drivers for self-tracking.

Keywords: healthcare information systems, health informatics, medical information systems, psychology, survey research, service science, service engineering

Introduction

In recent years, the possibilities of keeping records regarding daily activities, exercises, vital parameters, disease symptoms, nutrition, and much more increased remarkably due to new information technology, decreasing sensor size, and increasing smartphone usage. Consequently, the idea of garnering knowledge about oneself by quantifying and analyzing self-related data attracts an ever growing community of self-trackers.

In 2007, with the release of the first iPhone, a group of patients and individuals started self-tracking and recording data of their daily life by the help of smartphones and other technical devices within the scope of a philosophy they termed Quantified Self – QS for short (Kelly et al., 2007). QS members do not only create personalized healthcare data sets by collecting and analyzing their personal lives with apps and (partly self-developed) technical body measurement devices, they also share their own needs, developments, and ideas of individualized medical treatments in online and real-life meetings. They generally aim at optimizing their health, performance, or every-day life with a chronic disease by analyzing statistics and using new technologies – all self-motivated, voluntarily, and autonomously (Wolf, 2008).

At the same time, healthcare professionals, academics, and policy makers attempt to transform healthcare delivery towards patient empowerment and involvement. For example, novel IT-based records such as electronic medical records, electronic patient records, and personal health records are increasingly used (Mandl and Kohane, 2008). Though discussed controversially, healthcare information systems (HIS) a frequently seen as having the potential to reduce healthcare costs and improve outcomes in many application areas – see Fichman et al. (2011) and Black et al. (2011) for overviews. Particularly, in primary care the improvements are not fully validated (Bélanger et al., 2012). In remote health monitoring (RHM), however, the potential is already exploited and patients living at home may benefit from these technology-driven changes in healthcare delivery (Singh et al., 2011). The potential of HIS attracts healthcare professionals, academia, patients themselves and, more generally, health-oriented individuals. This individual awareness and willingness to manage one's own health opens up new perspectives that need to be considered from the professional's perspective.

These new perspectives include exploiting existing data sets and obtaining new data more easily. On the one hand, any data that patients have already been collecting voluntarily might be used to treat a disease or monitor its progress without additional effort. The existing data can also be further distributed to other healthcare stakeholders, for example, the involved therapists and care-giving relatives. On the other hand, many outpatient treatments, like RHM, rely on patient participation and ambulatory assessment (AA). Here, addressing "self-tracking traits" might provide better results in terms of secondary prevention or monitoring data quality. Even though the QS movement has become a phenomenon of health-conscious, achievement-oriented and self-efficient individuals around the world (TheEconomist, 2012), a profound understanding of these self-trackers, their activities, and their motivations is lacking. Therefore, we conducted a study among self-trackers to shed light on their profiles, activities, and motivations for self-tracking. We were guided by the research question: What are the underlying motivations of self-triggered health monitoring?

This paper presents the foundations for and the findings of the study among self-trackers. Following the scale development methodology described by Hinkin (1998), qualitative research, pre-tests, and an online survey with 150 self-trackers led to the development of a profound psychometric scale and framework of five motivational factors. This framework is meant to help understanding self-tracking motivations in future research. In addition, the framework might become a tool for developers of HIS, RHM, and AA systems – systems that help garnering data of patients in real-life situations and in real-time (Trull and Ebner-Priemer, 2012) – in their aim to design and provide systems and services that are widely accepted by patients. With this, we are contributing to the research agenda put forward by Agarwal et al. (2010) in extending the traditional realm of health IT and supporting HIS design.

Related Work

There is a wide field of literature regarding healthcare information systems, e.g. on the management of health information across computerized systems and its secure exchange (Haux, 2006; Kelley et al., 2011). The majority of these approaches introduce IT to enhance existing healthcare delivery processes and information exchange between healthcare professionals. Such an exchange of information between healthcare professionals is out of scope for this paper. It targets rather patient-centered health information systems including data generated by patients that track themselves. As described by Paré et al. (2007) in their systematic review, even the more patient-centered approaches rather statically collect information in medical records. These records can be enriched by the contribution of real-time health information and extensive measurements collected continuously by the patients themselves (Shin, 2012; Trull and Ebner-Priemer, 2012). One first step towards achieving this goal is provided by online health communities, in which patients share and discuss their health information (Eysenbach, 2008). Connecting the patient-initiated tracking data to health information systems majorly used by physicians is not yet accomplished (Singh et al., 2011).

Physician-initiated tracking. Several approaches exist where physicians ask their patients to track their health and make the information available to the physician. Remote Health Monitoring (RHM), sometimes referred to as Remote Patient Monitoring or Telemonitoring, presupposes a physical distance between patient and physician that inherently impairs classical healthcare (Paré et al., 2007). RHM comprises all professional activities that help redressing this distance by monitoring typical vital, physiological, and biological data, e.g., at a patient's home by the aid of static, mobile, or wearable sensors and devices. The automated or manual transmission of all garnered data to the physician in charge intends to ensure high quality healthcare (Schmidt et al., 2010). The aim is to provide "more regular and continuous information on vital signs which has the potential to reduce acute exacerbations" (Trueman, 2009). Permanent or temporary monitoring of patients in their typical environment has been found applicable especially for chronic diseases such as adiposity, hypertension, diabetes, respiratory conditions, or chronic heart failure. Particularly for the latter three, RHM's positive effects regarding patient empowerment and health have been reported multiple times (Chaudhry et al., 2007; Jaana and Paré, 2007; Jaana et al., 2009; Polisena et al., 2010).

Closely related to RHM is the notion of Ambulatory Assessment (AA). AA refers to patients garnering data in real-time in their natural environment (Trull and Ebner-Priemer, 2012). It promises "to minimize retrospective biases while gathering ecologically valid data, including self-reports, physiological or biological data, and observed behavior, for example, from daily life experiences" (Trull and Ebner-Priemer, 2012). AA therefore focusses on (semi-)automated, fast accessible and IT-based systems that help collecting data in real-time and real-life constraints (Ebner-Priemer and Kubiak, 2007). Health records and analytic systems help assessing physiological and vital parameters under everyday conditions, inter alia, the electrocardiogram (heart rate), blood pressure, respiration, skin temperature, and movements (Fahrenberg et al., 2007).

RHM and AA are prominent for but not limited to chronic diseases. They are additionally applied for preventive healthcare. A wide range of portable data recording systems has been developed that consider environment and social interactions, special habits, and mood changes (Mehl and Holleran, 2007).

Patient-initiated tracking. In addition to physician-initiated tracking, more and more people become self-responsible for their health and start tracking themselves – without a healthcare professional suggesting data collection, they start quantifying themselves out of intrinsic motivation. Patient-initiated tracking and information management, such as Health 2.0 (Eysenbach, 2008), Health Social Networks (Eysenbach, 2008; Free et al., 2010; Istepanaian and Zhang, 2012; Swan, 2009), and mHealth (Free et al., 2010; Istepanaian and Zhang, 2012) can add valuable health information for usage by patients themselves and by health professionals.

Health Social Networks, like PatientsLikeMe[1] and CureTogether[2], form a special type of social network that – besides being an online community – accumulate the members' vital parameters such as body weight, height, blood pressure, heart rate, and much more. This "new class of patient-driven healthcare services is emerging to supplement and extend traditional healthcare delivery models and empower patient self-care" (Swan, 2009, p. 492). The term self-tracking thereby refers to all actions of regular, voluntary elicitation and collection of all kind of metrics that can be related to a person. These metrics consist of daily-life parameters covering health, well-being, fun, behavioral, or environmental aspects of their lives

[1] www.patientslikeme.com, retrieved May 1, 2013.
[2] www.curetogether.com, retrieved May 1, 2013.

(Swan, 2009, p. 509). Examples relevant to healthcare include tracking of controlled or reflected health conditions, disease symptoms, medication, body weight, sleep quantity and quality, blood test results, blood pressure, nutrition, habits, and mood.

When patients track their lives, their behavior, or their habits, they "quantify" themselves. The term of Quantified Self (QS) evolved in 2007, when the American journalists and publishers of The Wired Magazine, Gary Wolf and Kevin Kelly, founded the blog QuantifiedSelf.com, which remains the most important website and central hub within the QS Community till today (TheEconomist, 2012). Today, the term *Quantified Self* addresses two dimensions of this movement. First, it includes the idea of garnering knowledge about oneself by *quantifying* and analyzing *self*-related data as it is declared in the credo "self-knowledge through numbers" (Wolf, 2008). Second, people that keep records of certain aspects of their lives form a worldwide connected community under the name "Quantified Self" (Butterfield, 2012). This community as an entity is connected via the central website QuantifiedSelf.com, via official and private blogs, in social networks as in Facebook groups, but also in real-life so-called "Meetup Groups" and regional and global conferences (Kelly et al., 2007). Meetup.com reports about 20.000 self-trackers[3]. Fox and Duggan (2013) estimate that already 69% of U.S. adults track health indicators for themselves or loved ones and one in five thereof uses technology to do so.

Due to its relative novelty, QS and health social networks – especially their members' motivations to participate in self-tracking activities – are not yet well understood. Only few scientific papers study the phenomenon. The most prominent contribution so far was made by Swan (2009), who examined "Emerging Patient-Driven Health Care Models", specifically Health Social Networks, Consumer Personalized Medicine, and Quantified Self-Tracking. Swan reviews the field of patient-driven healthcare models qualitatively, identifies trends, and touches upon potential challenges. Building on her work, we proceed quantitatively by building a psychometric scale and framework to understand the motivations of patients to engage in patient-driven healthcare models.

To the best of our knowledge, so far no research has been published on motivational aspects and psychometric scales for self-tracking of health data.

Since the major challenges and research areas of both physician- and patient-initiated approaches are not merely technology but rather acceptance, compliance, privacy, and potentially sustainable business models (Trull and Ebner-Priemer, 2012) considering the intrinsic motivation of self-trackers may lead to more effective and efficient healthcare information systems and patient empowerment.

Research Methodology and Procedure

In order to understand the underlying motivations of self-triggered health monitoring, we conducted a structured survey among self-trackers. Specifically, we followed the methodology described by Hinkin (1998) with six consecutive steps: (1) item generation, (2) survey administration, (3) initial item reduction, (4) confirmatory factor analysis, (5) further construct validity assessment, and (6) replication. The last step is left for future research.

Step 1: Item generation. The construct of interest is the motivation of self-triggered health monitoring. To articulate the theoretical foundations of this construct, we proceeded deductively and inductively. We combined logical partitioning via a broad based review of extant scientific literature – especially focusing Quantified Self, on positive and motivational psychology, online communities, and social media. In addition, we grouped information from self-trackers, found on Web pages and blogs and, most importantly, in a series of semi-structured face-to-face expert interviews with members of the QS community (Hinkin, 1998).

With regards to literature specifically on Quantified Self, the following sources proved most valuable for our study: Swan (2009), Kelly (2007), Wolf (2008, 2010), Butterfield (2012), and Fox and Duggan (2013). Examples for the literature on positive and motivational psychology that was incorporated in our study include Csikszentmihalyi and Csikszentmihalyi (1975), Csikszentmihalyi (1997), and Levesque et al.

[3] http://quantified-self.meetup.com/all/, retrieved May 1, 2013.

(2010). On online communities and social media, examples for the literature reviewed are Ludford et al. (2004), Tedjamulia et al. (2005), Eysenbach (2008), and Preece and Shneiderman (2009). As this paper does not report a systematic literature review but survey research, this list of references is not exhaustive, but only serves as example to give the reader a taste of the different streams of research that were considered when looking for theoretical foundations and potential scales and items to include in our study.

According to Swan (2009), many different fields of self-tracking have been identified comparing various self-trackers' personal blogs (e.g. http://measuredme.com/, retrieved May 1, 2013) and recorded experience reports from the official Quantified Self website (http://quantifiedself.com/topics/videos/, retrieved May 1, 2013). This was complemented by news reports like The Economist (2012).

Scientific literature, Web pages, blogs, and news were used to first build a mind map of relevant topics in the context of self-tracking, e.g. parameters tracked, technologies used, motivations and hurdles for tracking and the like. In this process, scientific literature was used deductively, Web pages, blogs, and news inductively. The mind map was then used to draft an interview guide for semi-structured interviews along the structure sketched in Table 1. Six interviews were conducted face-to-face at the 4th Meetup of the *Quantified Self Berlin* Meetup Group in September 2012. Three interview partners had been holding stage presentations on their past self-tracking experiences during this event; the other three were attending the Meetup as regular participants. Interviews were transcribed and analyzed by the research team to extend, detail, and prioritize the mind map. This process resulted in a set of constructs and sub-constructs and a preliminary list of potential items that characterize these.

Table 1. Structure of the interview guide for expert interviews

Section	Underlying question	Explanation
1. **Introduction**		Welcome and screen-out: Is the respondent an actual self-tracker or not?
2. **Objects of tracking**	"What?"	Are the participants either tracking well-being or health-related parameters or both or not directly self-related? Which parameters are they tracking concretely? Do they maybe suffer from a chronic disease?
3. **Activity level**	"How much?"	How much time do self-trackers spend on self-tracking activities? For how long are they already self-tracking?
4. **Motivation**	"Why?"	What are the underlying and psychological motivations to include self-tracking activities in their daily lives?
5. **Hurdles**	"Why not (more)?"	What could be possible hurdles for self-trackers to keep on self-tracking?
6. **Technology used**	"How?"	How to self-trackers measure and record their life? Do they use specific tools and spend a lot of money on it or are they trying to keep it as simple as possible?
7. **Personalities**	"Who?"	Implies being a self-tracker several specific characteristics of the personality's dimensions?
8. **Demographics**	"Who?"	Standard questions on the demographic background of the participants: age, origin, income, occupation.
9. **Other**		Did you answer honestly? Are you paying attention? Do you want to participate in the lottery drawing for one out of three Amazon vouchers?

At this stage, the structure for the survey was developed and literature was screened for existing scales and items. To assess personality, for example, the short version of the Big Five Personalities Tests (BFI-10) has been added (Rammstedt and John, 2007). On the motivations – the core of the present study – there was no applicable scale readily available. Items were newly developed, following standard guidelines (e.g. Hinkin 1998). Conceptual and content validity of the preliminary items were assessed in two ways: First via peer-review by researchers from information systems and psychology (different from the research time) and, second, in a pre-test as suggested by Schriesheim et al. (1993), where items were administered to 20 self-trackers.

Based on this validity assessment, some items were changed, re-phrased, or dropped. A set of 31 items on motivation emerged, each scaled on a 5-point Likert-type scale labeled *disagree strongly*, *disagree a little*, *neither agree nor disagree*, *agree a little*, *agree strongly*. A list of 31 items is not parsimonious; however, an extensive list of items with proven content adequacy is beneficial for subsequent item reduction (Hinkin, 1998; Schriesheim et al., 1993).

Step 2: Survey administration. The items were administered to self-trackers in form of a structured online survey in English language during November 2012. Besides the items on motivations for self-tracking, the survey featured questions regarding the extent of self-tracking, the parameters tracked, technology used, demographics and personality traits of respondents. In addition, screening and control questions were employed to check validity of responses. The screening question assured that only respondents stating they would be tracking themselves were allowed to enter the survey. The first control question – inspired by the Instructional Manipulation Check (Oppenheimer et al., 2009) – had a 5-point scale and read "If you are paying attention to this survey, please check the second box from the right that reads 'Paying Attention'". The second control question read "Did you answer honestly throughout the questionnaire? – Yes or No". Respondents could answer the survey at their own pace; on average it took them 14.9 minutes (standard deviation 10.9).

Respondents were recruited offline and online via multiple channels: in-person Meetups related to self-tracking, Meetup.com online groups related to self-tracking, Facebook groups related to self-tracking and health-related community groups in general, Twitter with tracking-related hashtags and accounts. In these channels, the research team distributed the link to the online survey, asked for help in the, research and announced that three 50$ Amazon gift certificates would be raffled off among survey respondents who chose to provide their e-mail address (which was not mandatory, one could participate anonymously; e-mail addresses were not used to identify individual respondents). In addition, we asked self-trackers to support us in viral marketing: To send the survey link to their friends, post it in official and private blogs related to self-tracking, re-tweet it and the like. Thus, it is not possible to say who received an invitation and, hence, self-selection in participating in the survey cannot be measured. This recruitment procedure is prone to sampling bias. This is one of the key limitations of the present study. We cannot assure that the sample of respondents is representative for either the entire population of self-trackers or for the set of people who received an invitation to the survey. Given recruitment procedures, one might especially expect that the sample is geared towards younger, Internet-focused, community-oriented respondents. However, a representative sample cannot be assured with reasonable effort, as there neither is a full list of self-trackers, nor a random sampling procedure in this population or a clear overview on typical characteristics of self-trackers to compare against our sample.

A total of 411 respondents followed the link to the survey. 224 of them answered the screen-out question "Are you keeping records of or tracking anything that occurs in your life? – Yes or No" and indicated they would be self-tracking. 167 of them completed the entire survey (75% of screened respondents), the other 25% dropped out for unknown reason – it can be speculated that the survey became too tedious for them, they might have been interrupted by other activities, or experienced problems such as a loss of internet connection. From the partial data we obtained from these 57 dropped-out respondents, there is no reason to suspect any systematic bias related to the survey's content that caused the dropout.

Finally, 150 of the 167 complete respondents were attentive and honest according to the two control questions (67% of screened respondents). Data from these 150 respondents is analyzed. 150 observations are not excessive but sufficient for the following analyses (Guadagnoli and Velicer, 1988; Hinkin, 1998).

Step 3: Initial item reduction. We employed an exploratory principal component analysis (PCA) with orthogonal Varimax rotation to analyze the structure of the items and reduce the number of items for the final scale. The number of components to be extracted was determined to be 5 based on a parallel analysis (Horn, 1965).[4] Following Hinkin (1998), items were iteratively dropped when they had no major loading (≥0.4) on any component, low communality (<0.4), major cross-loadings (≥0.4), or a lack of content fit (one single item dropped for this last criterion). The parallel analysis was re-run on the reduced set of 19 items and confirmed the existence of 5 principal components. The resulting structure explains a total of

[4] Parallel analysis is generally seen as one of the best component extraction methods, particularly it is assumed to outperform the Kaiser-Guttmann eigenvalue greater one criterion and the scree test employed in some studies (Hayton, 2004). Parallel analysis generates random data following the same structure as the original data (sample size and number of variables) and numerically establishes typical eigenvalues from the random correlation matrices. Components in the sample data with eigenvalues greater than eigenvalues from random data are retained.

63% of item variance, exceeding the required target of 60% (Hinkin, 1998). Convergent validity of constructs was assessed using Cronbach's alpha (Nunnally, 1978). All components exceed the respective required target of 0.6 for exploratory studies and new scales (Robinson, 1991). Therefore, the constructs appear to have adequate internal consistency and possess content validity. Details are reported in the following section, especially Table 1.

Step 4: Confirmatory factor analysis. To further support the internal consistency of the scale, we conducted a confirmatory factor analysis on the same data set. The combination of an exploratory principal component analysis (PCA) and a confirmatory factor analysis might lead to confusion – the rationale is as follows: Our study is exploratory. For the field of quantified-self, there is not yet a strong theoretical foundation and this study aims at providing a building block for having such a theoretical foundation in the future. Thus, the exploratory PCA guides our analysis of the motivations for self-tracking. However, a PCA is not fully able to quantify the goodness of fit for the resulting structure (Hinkin, 1998; Long, 1983). The confirmatory factor analysis restricts each item to load only on a single component. The analysis is "a confirmation that the prior analysis have been conducted thoroughly and appropriately" (Hinkin, 1998). We used a reflective specification of the model. Both local and global quality criteria are satisfactory. Specifically, each item loads significantly on its component (at 1% level). $\chi 2$ divided by the degrees of freedom is 1.9 and, thus, less than the acceptable limit of 2 (Byrne, 1989, p. 55) or 5 (Browne et al., 1993, p. 144). The root mean square error of approximation (RMSEA) is 0.078 and, hence, below the acceptable limit of 0.08 (Browne et al., 1993, p. 144). As suggested by Hinkin (1998, p. 115), up to this point, we "can be relatively assured that the new scales possess content validity and internal consistency reliability."

Step 5: Further construct validity assessment. Criterion-related validity and discriminant validity were further assessed by relating the motivations to the intensity and object of tracking and by testing for correlations between motivations and personality traits. Results further strengthen the validity of the scales. Details are reported in the following section, especially Table 3 and Table 4.

Step 6: Replication. To date, the procedure relies on a single sample. The replication with an independent second sample will enhance external validity and generalizability (Hinkin, 1998; Stone and Stone Eugene, 1978). This step is left for future work and other researchers in order to rule out researcher bias.

Results of the Exploratory Survey

Descriptives

The characteristics of our sample are as follows (n=150): Age ranges from 14 to 76 years with mean 34 and median 30 years. 71% of respondents are between 20 and 40 years old. 58% are male, 37% female (5% did not disclose their gender); 41% are employed, 33% students, 17% self-employed, 9% other; 53% are from Europe, 39% from North America, 8% other.

The objects of tracking within the self-trackers differ in many ways. Some self-quantifiers suffer from chronic diseases and therefore keep records of their medication or occurring symptoms in different situations. Others are only tracking their daily steps or the running distances; still others are regularly recording their body weight or body mass index (BMI) and try to correlate it with environmental factors such as weather or GPS-tracked location. Respondents track 1 to 39 parameters (mean 9, median 8), mainly on physical activity (e.g., exercises, steps), body (e.g., weight, heart rate, blood pressure), well-being (e.g., sleep time and quality, mood), nutrition (e.g., calories intake and balance, water consumption), and medical issues (e.g., symptoms of chronic diseases, blood-test results, medication).

One third of our respondents suffer from a chronic disease. Out of these, 73% disclosed their diseases verbally in their response to an open-ended question. These chronic diseases are mainly rheumatoid arthritis, diabetes, and thyroid disorders.

Concerning the question, why they started tracking in the first place, 56% agreed that "they just thought they should" start self-tracking. Only 28% "have heard about QS before", 7% are influenced by "friends that started doing so as well" and 8% have been asked by their physician to start tracking some of their vital parameters or symptoms.[5] Comparing respondents that have started self-tracking before 2010 and after 2010[6] clearly indicates that respondents, that started tracking before QS became popular in the media, are less influenced by friends or news but are more likely to have being recommended conducting self-tracking by their physician (X^2 test; df = 4; p = 0.042). On the other hand since 2010 there have been more people that have heard about self-tracking in the news: 21% after 2010 compared to 7% of all respondents before 2010.

According to expert interviews with researchers and members of the QS community, these data are by and large in line with the common perception of self-trackers. Thus, while acknowledging the recruitment potential bias, we see the survey results as valuable, exploratory contribution in a field lacking research.

Five-Factor Framework of Self-Tracking Motivations

The main aim of this study is to understand the deeper underlying motivations of self-tracking: What exactly keeps a self-tracker working on his tracking activities? Is he or she rather driven by the fun and entertaining aspects of self-tracking or rather by a strong self-responsibility and willingness to reach personal goals?

A self-tracking motivation model with five motivations has been developed with the help of an exploratory principal component analysis (PCA) on responses from 150 self-trackers to an online survey. The model includes a set of 19 question items by which the motivational aspects of *Self-entertainment*, *Self-association, Self-design, Self-discipline,* and *Self-healing* on self-tracking can be measured. Table 2 provides key statistics on the results of the PCA.

Factor 1: Self-entertainment *– motivated due to the "pleasure-bringing" aspects of self-tracking*

The first component of the PCA deals with the enjoyment, fun, and ludic aspects of self-tracking. The motivation by *Self-entertainment* refers to the fun of one's preoccupation with a technical device or the enjoyment of playing around with numbers and statistics of one's own-related data. Some of the items refer to the state of *flow* as described by Csikszentmihalyi and Csikszentmihalyi (1975), a mental state characterized by the experience of forgetting about time and getting lost in the respected activities (Csikszentmihalyi, 1997).

The questionnaire contained an open-ended question for the respondent's motivation prior to suggesting motivations and asking for their applicability in closed Likert-type questions. Answers to this open-ended question further illustrate the factors – they include the following: "*I like mapping and data. I collect my own data so I can play around with it*" (Participant #277), and "*I have always been curious about measuring everything even without any special purpose. I found that you learn a lot from data even when you were not searching anything special. I like QS for QS sake, not just for solving problems*" (Participant #403).

Factor 2: Self-association *– motivated by the prospect of community citizenship and self-individualizing aspects within a community*

The second factor mainly differs from the other factors as this has less to do with one's *self* but with one's relation towards a community and with others. The term S*elf-association* is a combination of the words *association* (which can concurrently mean community, affiliation and resemblance) and *self*. This motivation comes from the idea, that there is no individuality without community; every self-tracker needs a counterpart to understand him- or herself – mainly by comparison. Thus, this factor does not necessarily mean that a self-tracker needs the community to satisfy a certain sense of belonging but rather implies a self-tracker's need to understand his individuality within a respective environment. Future HIS should

[5] From data analysis, we have no indication that self-trackers triggered by their physician are different from self-trackers without physician stimulus. Thus, we pool the data. This can be seen as support for generalizing results to physician-initiated tracking. However, the sample of respondents with physician-initiated tracking is too small to statistically assert equality of the groups.

[6] In 2010, the first journalistic reviews of the Quantified Self movement in the US can be found on the Internet. Thus, it might be an interesting inflection point to distinguish people starting self-tracking before or after the media hype.

consider patients' interest in comparing their results to others. They also should include functions that serve today's patients' need to present themselves and their belief to be able to help and/or inspire others.

Participant #310 responded he would be self-tracking "*... to be able to see my personal evolution and the activities of my friends or people who have the same interests*".

Table 2. Rotated component matrix of the exploratory principal component analysis
(Varimax rotation with Kaiser normalization; major loading in bold font, cross-loadings in grey font)

	I'm self-tracking because ...	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Commu-nality	Cronbach's alpha
Self-entertainment	... I enjoy getting lost totally in self-tracking activities. (#01)	**.77**	.06	.11	-.12	.31	.71	.78
	... I like playing around with numbers/statistics etc. (#02)	**.73**	.13	.16	.06	-.08	.59	
	... I like playing around with my smartphone/technical device etc. (#03)	**.72**	.11	.24	.14	-.19	.64	
	... I enjoy forgetting about time while doing so. (#04)	**.68**	.04	.00	-.12	.34	.59	
	... it is fun and entertaining. (#05)	**.60**	.22	-.09	.34	-.07	.54	
Self-association	... I want to help/inspire others. (#06)	-.01	**.85**	.11	.1	.12	.76	.82
	... the way I'm doing it is interesting for others/might help others. (#07)	.18	**.83**	.19	-.06	.11	.77	
	... I want to compare my results to others. (#08)	.15	**.74**	.00	.25	.03	.64	
	... I want to present myself to others. (#09)	.28	**.58**	.25	.31	-.04	.57	
Self-design	... I want to control what I'm doing with my life. (#10)	.03	.06	**.75**	.28	.11	.66	.73
	... I try to manipulate certain aspects in my life. (#11)	.14	-.05	**.73**	.02	.14	.57	
	... I enjoy being my own master. (#12)	.25	.27	**.61**	.30	-.01	.60	
	... I'm interested in how certain things in (my) life interact. (#13)	.25	.20	**.57**	-.14	.03	.44	
	... it helps me to optimize the way I'm living. (#14)	-.15	.21	**.56**	.30	.04	.47	
Self-discipline	... it motivates me to keep on working for a goal. (#15)	-.03	.21	.14	**.78**	.05	.68	.68
	... It allows me to reward myself. (#16)	.36	.10	.04	**.69**	.16	.64	
	... it facilitates my self-discipline. (#17)	-.10	.07	.37	**.67**	.11	.62	
Self-healing	... I don't trust in the healthcare system/classic therapies. (#18)	.06	.11	.08	.12	**.86**	.78	.80
	... I want to be independent from traditional medical treatments. (#19)	.04	.07	.15	.12	**.85**	.77	
	Eigenvalue	2.91	2.62	2.52	2.19	1.82		
	Share of variance explained	.15	.14	.13	.12	.10		
	Cumulative share of variance explained	.15	.29	.42	.54	.63		

Factor 3: Self-design *– motivated by the possibilities of self-optimization*

A total of five items load into this factor. *Self-design* applies to the self-optimization dimension by self-tracking. No matter whether it is a self-tracker's health, fitness, or mood, generally self-trackers are fascinated by the idea of controlling the way they are living by taking responsibility and optimizing their own lives. At the same time, self-trackers that are strongly motivated by the prospects of self-design are driven by a need to feel special towards other people (Ludford et al., 2004). Future patients might be seen as interested in body and brain tuning and willed to optimize their performance self-reliantly, for example by understanding how certain things in life interact.

Quotes exemplifying this motivation are "*I wasn't satisfied with my status quo. I wanted more from my body and my brain*" (Participant #251) and "*[...] via self-tracking I can identify factors and traits that mostly affect my everyday behavior and mental/cognitive/physical state, so I could optimize my life by controlling and manipulating those factors*", (Participant #109).

Factor 4: Self-discipline *– motivated due to the self-gratification possibilities of self-tracking*

In contrast to Self-design, *Self-discipline* refers to the rewarding and promising aspects of self-tracking, which might be the prospect of attaining a goal, obtaining a reward, or avoiding a penalty or a negative consequence (Levesque et al., 2010). Three items load on this component: The facilitation of self-discipline, motivation to keep on working for a goal, and potential to reward oneself. According to Preece and Shneiderman (2009), self-disciplining by goal-orientation and a certain need to achieve may increase the possibility of becoming an actual *contributor* to a community. People that are motivated by self-disciplining through self-tracking may "[...] find it enjoyable to work hard, to be compared to a standard and to be challenged" (Tedjamulia et al., 2005). Future patients might be willed to collaborate rather when they experience themselves that self-tracking helps them disciplining, rewarding and motivating themselves.

Participant #211 wrote that "self-tracking helps to motivate me to reach for and achieve certain goals".

Factor 5: Self-healing *– motivated by the self-healing possibilities of self-tracking*

The search of individual therapy alternatives as well as a certain rebellion against the healthcare system is part of this factor. Self-trackers that are motivated by *self-healing* "... don't trust in the healthcare system" and "... want to be independent from traditional medical treatments". According to Wolf (2010) human beings want to understand more and more how they are different from others and how different therapy alternatives may apply to them. This factor thus represents an increased health-awareness that leads to a greater need of understanding one's individual standing in a community and willingness to invest in one's health – consciously and demandingly. Future generations of HIS may focus on creating and adding value for the patients themselves by the provision with new information about themselves.

Quotes exemplifying this motivation are "*I want to know if any number of symptoms are related to each other, as well as to record facts that I can use to communicate to health professionals or remind myself of activities from year to year*", (Participant #207) or "*Essentially, doctors and personal fitness coaches have been unable to help. I suffered from insomnia, and found through self-tracking that blackout curtains helped best*" (Participant #126).

Construct Validity Assessment

The rigorous scale development methodology with its exploratory principal component analysis and confirmatory factor analysis suggest that the five-factor framework of self-tracking motivations possesses content validity and internal consistency reliability (cf. Section on Research Methodology and Procedure). This section presents further tests of criterion-related and discriminant validity.

Motivation and intensity of tracking

Intuitively, one should expect that more motivation leads to more activity. This holds true for each of the five motivational factors individually and – assuming an underlying additive structure of motivation – for all five motivational factors jointly. We tested this by investigating the relation of motivation and the intensity of tracking.

Intensity is operationalized by two factors elicited in the survey: The number of parameters a respondent tracks and the time he or she spends on self-tracking. The number of parameters ranges from 1 to 39 (mean 9, median 8). If, e.g., a respondent stated he would be tracking his steps, weight, and symptoms of chronic diseases, this is coded as 3 distinct parameters. Responses were elicited by suggesting a list of 45 parameters frequently tracked by self-trackers. Parameters were grouped in nine groups (physical activities, body, nutrition, well-being, addictions, medical, environment, relationships, other), respondents could check multiple parameters and each parameter group featured an "other" option with a free text input. Time spend on self-tracking was elicited with free text fields asking for the number of hours and minutes per day spend on self-tracking. The average time per day is 95 minutes (median 30 minutes). As data is highly non-normal, a log transformation is applied to the time spend on tracking.

The hypothesis is that motivation increases time spent on tracking. This effect might (partially) be mediated by the number of parameters tracked. Causal mediation analysis investigates this relationship (Baron and Kenny, 1986; Hayes, 2009). Figure 1 sketches the research model and summarizes the results: Motivations do indeed have a significant effect on activity. Higher scores on any of the motivational factors significantly increases the number of parameters tracked. When regressing the log of time spent on self-tracking on the motivations, higher scores on any of the motivational factors significantly increases the time spent on tracking (data not shown). This effect is partially mediated by the number of parameters tracked.

In the mediation model, only self-association retains a significant direct effect on time spent beyond the mediation effect via number of parameters tracked. The interpretation appears straight forward: Self-association has a community element which requires time to present oneself, to compare oneself to others, and to digest feedback from the community.

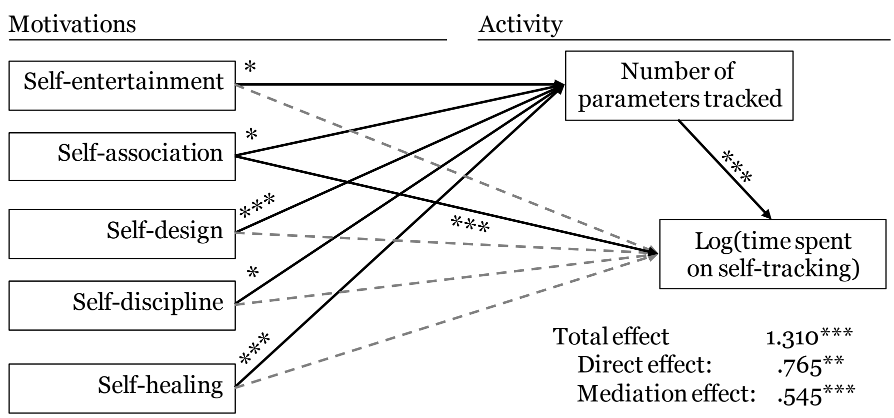

Figure 1. Causal mediation analysis to assess criterion-related validity of the Five-Factor Framework of Self-Tracking Motivations

Significance codes: '***' .001 '**' .01 '*' .05;
grey, dashed arrows indicate insignificant relationships

Overall, the mediation analysis supports criterion-related validity. The motivational scale does not only measure reliably, its measurement has predictive power for behavior. In addition, data supports the notion of a cumulative / additive structure of motivation for self-tracking.

Motivation and object of tracking

Self-trackers differ with respect to their motivational profile: some are more driven by Self-entertainment, some by Self-healing etc. In addition, self-trackers differ in the focus of their tracking: Some focus on physical activities, others on nutrition, even others focus on other parameters. One should expect a relationship of these two factors: motivation and object of tracking. We investigate this relationship by a series of logit regressions.

The parameters tracked by respondents are grouped in nine clusters of parameters. This grouping bases on pre-tests and was displayed in the survey. For the present analysis, we run a separate logit regression for each of these nine groups. The dependent variable is a binary dummy indicating whether a respondent tracks at least one parameter in the group (dummy value 1) or not (dummy value 0). Independent variables are the five motivational factors. Wald tests are performed for individual coefficients, likelihood ratio tests for the overall model. Table 3 summarizes the results from regression analysis.

119 out of 150 respondents track at least one parameter on their physical activity; whether an individual self-tracker does so, is significantly influenced by his or her self-discipline (model 1 in Table 3). The other

four motivational factors have no significant influence on tracking physical parameters. Thus, if one engineers a system or service that relies on tracking physical activities, one has to appeal to participants' desire for self-discipline and rewarding themselves. Promoting features of the system or service that refer to self-entertainment, self-association, self-design, or self-healing will be less effective in convincing participants to track their physical activity. The same holds true for tracking body parameters (model 2).

A system or service engineer trying to motivate tracking of well-being (model 3), nutrition (model 4) or medical aspects of daily live (model 5) will be most effective when appealing to a combination of Self-design and Self-healing. For nutrition, referring to Self-discipline will further increase the likelihood of tracking the intended parameters. For tracking medication, symptoms, or other medical parameters, referring to Self-discipline has the opposite effect – it significantly decreases the likelihood of tracking the intended parameters. For well-being, the Self-discipline factor is irrelevant.

Table 3. Regression of the object of tracking on motivational factors

Logit regression coefficients (standard errors)

Significance codes: '***' .001 '**' .01 '*' .05; significant coefficients in bold font

	(1) Physical activities	(2) Body	(3) Well-being	(4) Nutrition	(5) Medical	(6) Environ-ment	(7) Addictions	(8) Relation-ships	(9) Other
Number of respondents	150	150	150	150	150	150	150	150	150
Number of respondents tracking ≥ 1 parameter	119	110	89	67	51	38	31	24	106
Self-entertainment	.327 (.212)	.022 (.187)	.194 (.178)	-.282 (.190)	-.095 (.187)	**.646** (.210)**	-.212 (.219)	.128 (.229)	-.335 (.190)
Self-association	.279 (.220)	.356 (.198)	.227 (.175)	.118 (.188)	.085 (.192)	.300 (.199)	**.518* (.218)**	.024 (.229)	.251 (.192)
Self-design	.328 (.206)	.136 (.185)	**.408* (.178)**	**.388* (.192)**	**.654** (.223)**	.247 (.209)	.459 (.240)	.308 (.246)	.366 (.191)
Self-discipline	**.714*** (.215)**	**.449* (.189)**	-.143 (.176)	**.448* (.194)**	**-.389* (.194)**	-.004 (.206)	.254 (.230)	.213 (.243)	.249 (.184)
Self-healing	.457 (.245)	.259 (.204)	**.369* (.181)**	**.877*** (.214)**	**.738*** (.204)**	.037 (.191)	.290 (.205)	.215 (.219)	-.226 (.190)
Intercept	**1.595*** (.244)**	**1.099*** (.199)**	**.410* (.175)**	-.264 (.184)	**-.818*** (.199)**	**-1.211*** (.209)**	**-1.525*** (.234)**	**-1.724*** (.236)**	**.956*** (.192)**
Nagelkerke's R^2	.197**	.103	.114*	.255***	.234***	.131*	.134*	.042	.108*

Interestingly, Self-entertainment only affects tracking of one's environment (model 6) and Self-association the tracking of addictions (model 7). For the latter, a causal relationship seems unlikely. It appears to rather be a case of common cause: People who value association with a community or group might be more prone to consumption of coffee, cigarettes, and alcohol (the main addiction parameters tracked) and, thus, more likely to track these parameters. For relationships (model 8) and other parameters like to-do lists and finances (model 9), none of the motivational factors has a significant impact. Likely as the number of respondents tracking relationships is too small and other parameters are too diverse.

Overall, relating the object of tracking to motivational factors is interesting for two reasons: Firstly, the existence of significant effects adds to the evidence of criterion-related validity. Secondly, data provides guidance how to motivate people for self-tracking given a specific type of tracking one wants to inspire.

Motivation, personality, and demographics

For the validation of novel measures, convergent as well as discriminant validation is required (Campbell and Fiske, 1959). Discriminant validity tests whether a novel measure is highly related to existing measures. If, the five motivational factors proposed in this paper would be highly correlated with established scales, their value would be marginal, as other scales could be used for the same purpose.

Key candidates for testing discriminant validity of the new scale are personality traits and demographics. The big five personality traits (extraversion, agreeableness, conscientiousness, neuroticism, openness) were measured with the short scale validated by (Rammstedt and John, 2007). Demographics were elicited as age in years and gender. Females are coded as unity, males as zero. 7 respondents did not disclose their gender; they are excluded for correlating gender with motivation. Table 4 shows the results.[7]

Correlation of motivational factors with either common personality traits or demographic characteristics is generally low and ranges from -.244 to .209. Most correlations are not significantly different from zero. Thus, we conjecture that the motivational scale for self-tracking has discriminant validity.

Table 4. Correlation of motivational factors and personality traits

Pearson's product moment correlation, n = 150 (For gender: point-biserial correlation, n = 143)

Significance codes: '***' .001 '**' .01 '*' .05; significant coefficients in bold font

	Extraversion	Agreeableness	Conscientiousness	Neuroticism	Openness	Age	Gender (female = 1)
Self-entertainment	-.130	-.134	-.024	-.018	-.025	.086	**-.244***
Self-association	**.162***	.020	.107	**-.161***	.093	-.008	-.155
Self-design	.036	**-.167***	-.017	**.191***	**.209***	.157	-.019
Self-discipline	.023	-.156	.107	-.052	.038	-.123	-.119
Self-healing	**-.172***	.112	.068	.063	.116	.117	.105

Conclusion and Future Work

The revolutionary rise of smartphones together with today's ubiquitously available internet access has changed the healthcare delivery landscape. All of the new possibilities through technology have opened up a world that offers new ways to get to know oneself and to gain a profound, fact-based understanding of collected self-related data. Patients increasingly become empowered, self-dependent actors in the healthcare service system. They meticulously record numerous parameters that might be of high relevance for their physicians, including aspects of their physical activities, body, well-being, nutrition, medication, diagnostics, symptoms, environment, addictions, and the like. Since 2007, this manifests in the Quantified Self community.

In this paper we addressed the research question what the underlying motivations of self-triggered health monitoring are. In an exploratory survey among 150 self-trackers, we developed a Five-Factor-Framework of Self-Tracking Motivations and a psychometric scale with 19 items that cover the five factors of motivation. These factors are (1) Self-entertainment, (2) Self-association, (3) Self-design, (4) Self-discipline, and (5) Self-healing. Various methods were used to test convergent, discriminant, and criterion-related validity of the scale. Quality criteria meet all conventional targets. In brief, the scale seems to measure reliably, it measures something different than other scales, and its measure is meaningful for explaining intensity and type of self-tracking.

The present study has obvious shortcomings, most prominently a potential sampling bias and the lack of replication. The sample of respondents might not be representative for the entire population of self-trackers. This cannot be judged precisely, as there is neither a full list of self-trackers nor a clear overview on typical characteristics of self-trackers to compare against our sample. In addition, all our quantitative analysis relies only on a single sample. The replication with an independent second sample will enhance external validity and generalizability. It is up to future research to replicate the approach with different pools of respondents to support or refute our results.

[7] Correlation among motivational factors is zero by design (orthogonal rotation). Correlation among personality traits should be about zero and in fact is indistinguishable from zero for most cases (data not shown). Only exception: extraversion correlates positively with conscientiousness and openness and negatively with neuroticism.

The paper strongly focuses on patient-driven approaches and falls short of fully covering the extant theory and practice of health information systems centered on healthcare professionals. Legal and ethical dimensions of patient self-tracking have not been addressed. Despite all these obvious shortcomings, we believe that our exploratory empirical study is a valuable step in structuring and quantifying the motivations of self-trackers, a field of study that is relatively young and, so far, largely qualitative and anecdotal.

For health information systems, the question emerges what we can learn from self-trackers for the engineering of physician-initiated self-tracking systems like Remote Health Monitoring (RHM) or Ambulatory Assessment (AA). The results presented above lead to a three part answer to this question: First, we can conclude that self-tracking exists for a remarkably heterogeneous group of people. Self-trackers responding to our survey track up to 39 parameters of their daily life, and they include people from various countries and continents. The phenomenon exists from teenagers to senior citizens with no significant age effects and hardly any gender effects. Some self-trackers suffer from chronic diseases, others don't. In other words, self-tracking is a robust phenomenon. RHM and AA systems and services frequently suffer from compliance of patients with self-tracking guidelines suggested by health professionals. Learning from voluntary self-trackers, understanding their positive motivation for self-tracking, communicating it to people not directly convinced of the necessity, and using self-trackers as role models is the first implication for engineering RHM and AA systems and services.

Second, the Five-Factor-Framework of Self-Tracking Motivations provides structure. Data shows that more motivation on a single factor leads to increased tracking activity and, in addition, motivation from different factors is cumulative. Thus, the factors along with their description and survey items can inform engineers of HIS. Depending on the object of tracking (i.e. the parameter one wants people to track), different factors are relevant. The design of RHM and AA systems and services should appeal to the respective motivations to foster patient compliance.

Third, this structure supports marketing in targeting the right patient or customer population, screening potential users, and to tailor communication of the benefits of RHM and AA solutions. After deployment of a solution, the Five-Factor-Framework can support tracking adoption. Apart from the particular HIS-perspective, the framework can also support healthcare delivery in general. If used by healthcare service providers like physicians and therapists, they might incite the patients to improve secondary prevention or monitoring data quality.

In summary, the implication for healthcare information systems is that engineers and developers can learn how to motivate people to track themselves, how to design systems that appeal to intrinsic motivators, and how to plan and control implementation success. However, all of these aspects warrant further research and proof in practical applications.

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