The Role of Self-Control in Self-Tracking

Completed Research Paper

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Abstract

Self-tracking is defined as using technology to monitor one's own behaviour e.g. sleeping habits or steps. Using established measurements from psychology we investigate how different levels of self-control influence the tracking behaviour of consumers and their expenditures for self-tracking software and hardware. Furthermore, we analyse what motivations to start self-tracking drive different self-tracking activities. To this end we conducted a web-based survey with 130 participants and evaluated our data using PLS-SEM analysis. We find that higher levels of self-control increase the odds of consumers tracking physical parameters and spending more for self-tracking software and hardware. Furthermore, higher impulsivity has a negative effect on the likelihood of tracking medical parameters. Tracking behaviour in general is driven by curiosity. Overall expenditures depend on the usage frequency of self-tracking tools. We conclude that users with low self-control value self-tracking to a lower degree because they are confronted with negative self-tracking results and emotions.

Keywords: Self-Tracking, Self-Control, Impulsivity, IS Adoption, Value of IS, Quantified Self

Introduction

New information technology, increased smartphone usage and decreased sensor sizes have accelerated the rise of the self-tracking movement in the last years (Gimpel et al. 2013). Thereby, not only consumers are interested in quantifying the self, also insurance companies support the adoption and use of their clients' self-tracking tools. (AOK 2015; Gröger 2014). Some organisations even support the adoption of self-tracking as a health protection intervention for their workforce (Nikayin et al. 2014).

Self-tracking is thereby defined as using technology to monitor one's own behaviour, e.g. sleeping habits, steps or activities (Choe et al. 2014). While self-tracking is a relatively new concept, self-monitoring in the area of behavioural psychology goes back to 1970 (Kopp 1988) and is used within the scope of cognitive behaviour therapy, e.g. for the control of thoughts, emotions, food intake and behaviour (Spahn et al. 2010). The underlying philosophy of behaviour therapy is thereby to teach individuals to self-monitor, identify and analyse dysfunctional patterns of thinking or acting and to foster behavioural changes (Spahn et al., 2010). Increased self-awareness through self-monitoring thereby facilitates the intended behaviour change (Burke et al. 2009; Wilde and Garvin 2007). Thereby, clinicians play an important role for self-monitoring in the context of cognitive behaviour therapy but the basic ideas of self-monitoring and self-tracking are very similar (Choe et al. 2014).

While the benefit of self-monitoring is acknowledged in a multitude of settings like e.g. obesity, smoking and drinking (Lipinski et al. 1975; Sobell and Sobell 1973; Spahn et al. 2010) other studies have failed to demonstrate the reactivity of self-monitoring (Bellack 1976; Fremouw and Brown 1980). Furthermore, Selimbegović and Chatard (2013) found out that self-awareness has a positive effect on the accessibility of suicidal thoughts, if the self is not coming up to own standards. In the case of self-tracking, Sjöklint et al. (2015) also demonstrate that the confrontation of not reaching the set self-tracking goals induces the effort to find coping strategies. Because self-monitoring as well as self-tracking can lead to favourable but also unfavourable reactions in individuals, we address the question of what user characteristics influence the appreciation of self-tracking. While Gimpel et al. (2013) and Choe et. al (2014) investigated motivational factors to start with self-tracking in the context of the Quantified Self community, Shin et al. (2015) suggested that there is a difference between Quantified-Selfers and usual self-trackers. Quantified-Selfers constantly seeking more accurate ways to measure different parameters, are fascinated with data generation and are more open to share personal data on social media platforms. In a qualitative investigation they found out that curiosity is the prior motivation to adopt self-tracking for usual self-tracking users. We want to supplement this research through a quantitative investigation of different motivations for diverse self-tracking activities of usual self-trackers.

Because Yu et al. (2015) suggest that people who have previously failed to reach their goal have more difficulties regarding self-monitoring, we assume that people who are more likely to achieve their goals value self-tracking to a higher degree because the risk of failure and cognitive dissonance (a psychological discomfort triggered by e.g. a discrepancy between goals and behaviour (Festinger 1962)) is much lower. Thereby, Tangney et al. (2004) found out that high levels of self-control have a positive impact on goal achievement in a variety of settings.

The objective of this study is therefore to find out whether people who have more self-control are more likely to pursue specific self-tracking activities and spend more money on self-tracking products. These are critical questions because the understanding of important user characteristics is fundamental for re-examining the current design of self-tracking technologies (Choe et al. 2014).

This leads to our research questions:

1. *How do different motivations to start self-tracking drive the actual tracking activates of users?*
2. *Is there a relationship between higher levels of self-control capabilities and the pursued self-tracking activities?*
3. *Do consumers with higher levels of self-control spend more money on self-tracking technologies?*

To answer these questions, we conducted a survey with 130 participants. The survey included the two-factor version of the Brief Self-Control Scale by Maloney et al. (2012) adapted from Tangney et al. (2004) and questions about the utilisation of self-tracking tools, as well as questions regarding the expenditures for self-tracking. We analyse the data of the survey by using partial least squares path modelling (PLS-SEM).

The remainder of this paper is structured as follows. First, we provide the theoretical background and related work of self-tracking, self-monitoring and self-control. Second, we describe our research methodology. The following chapters present the results and the analysis of our findings. We conclude with a short discussion, the implications of our results and the limitations of our study

Theoretical Background and Related Work

Quantified Self

In the year 2007, Gary Wolf and Kevin Kelly started the Quantified Self movement with the launch of the first Quantified Self blog. The members of this community participate in a wide range of activities like e.g. worldwide in-person meetings to share knowledge and talk about self-tracking experiences (Gimpel et al. 2013). Quantified Self is thereby an umbrella term which refers to the Quantified Self community as well as the activity of self-tracking (Choe et al 2014). Self-tracking is defined as using technology to collect personally relevant information for the purpose of self-reflection and self-knowledge (Choe et al. 2014; Li et al. 2010). To meet the needs of different users tracking a wide variety of parameters, several self-tracking device categories exist. Table 1 gives an overview of those hardware categories and exemplifies possible use-cases in the Quantified Self context.

In recent years, the body of literature in the area of Quantified Self has been growing. The rise of consumer-orientated hardware like smart watches and fitness bands currently propels Quantified Self from a niche topic to the centre stage in different streams of research. Gimpel et al. (2013) investigated the motivational factors for participating in the Quantified Self community. They found out that the factors self-entertainment, self-association, self-design, self-discipline and self-healing are important motives. In a later qualitative investigation, Shin et al. (2015) found out that there is a difference between the usual self-tracking users and participants of the Quantified Self community (Quantified-Selfer). They suggest that Quantified-Selfers constantly search for more accurate ways of measuring many aspects about themselves by using various devices and mobile applications. Furthermore, they are fascinated by the generated data and they are more open to sharing personal data on social platforms. Therefore, the discovered motivational factors *curiosity* about the device and about the own activity pattern were not fully applicable to Quantified-Selfers.

Table 1. Device Classification

Device Category	**Description**
Portable / Software	Portable devices like e.g. mobile phones are not directly worn on or attached to the body, but have to be carried by the consumer; their functions are usually used on-demand and they are easily manageable. They primarily contain data, which are manually inserted e.g. tracking data about mood or emotional status.
Wearable	Wearables are functional computers, which are worn near to the body. They provide on-demand and passive always-on sensor-based data collection features, which require close proximity to the body e.g. recording of heart rate or pulse. Smart watches or fitness trackers are examples of wearables.
Placeable	Placeable devices are devices that are strategically placed on relevant locations for the tracking of specific activities. They are useful for monitoring the behaviour of persons and can be located e.g. on objects a person interacts with. Examples of placeable devices are wirelessly connected treadmills or weight scales.
Consumable	Consumable devices are located within the body. Currently, they exist only within the medical or military domain. They are tiny in size and have therefore no long battery life.
Implantable	Implantable devices are similar to consumable devices but they have more longevity. The purpose of these devices is to monitor critical health parameters.

Table 1. Device Classification (adapted from Trickler 2013)

Furthermore, Shin et al. (2015) investigated motivational factors of usual self-tracking users. Some people thereby have an intrinsic motivation to pursue physical activities while others have no intrinsic motivation. They moreover differentiate between people that are motivated by the device and people who are not motivated by the device. In our research, we want to complement these results by finding out what kinds of motivations and intentions lead to self-tracking different parameter categories and what kind of people value self-tracking the most.

Self-Monitoring

While Quantified Self is a relatively new concept, self-monitoring is a basic clinical technique used in cognitive-behavioural therapy (Cohen et al. 2013). This technique was first introduced by Kanfer (1970) and involves the systematic observation and recording of e.g. thoughts, emotions, and problematic behaviour (Cohen et al. 2013; Spahn et al. 2010). The increased awareness fostered by self-monitoring leads to a comparison of the own self to own standards and is an important factor for promoting behavioural change (Burke et al. 2009; Wilde and Garvin 2007). Multiple studies found a significant relationship between self-monitoring and behavioural change (Boutelle et al. 1999; Milas et al. 1995; Tate et al. 2003). On the other hand, Fremouw and Brown (1980) found contradictory results with respect to the functionality of self-monitoring in their analysis of earlier investigations. Yu et al. (2015) suggest that some people are confronted with more challenges as to self-monitoring than others. Especially people who previously failed to achieve a goal have greater difficulties with self-monitoring. Furthermore, Duval et al. (1992) found out that people who perceive a discrepancy between their self and their own standards try to adapt to the standard if the outcome expectancy is positive. In the case of a negative outcome expectancy, people try to withdraw from the situation. Festinger (1962) thereby shows that a discrepancy between two cognitions, e.g. the behaviour and the attitude, leads to cognitive dissonance and negative emotions. In line with these findings, we expect that people who are more likely to achieve their goals find specific self-tracking activities more attractive than people who are confronted with failure and the associated negative emotions. Tangney et al. (2004) show a significant relationship between self-control and higher achievements in a variety of settings (e.g. better academic achievements as well as less binge eating) and therefore we assume that people with a higher degree of self-control also spend overall more money on self-tracking products.

Self-Control

Self-control is defined as the ability to modify and adjust the self as well as interrupt undesired behavioural tendencies (Tangney et al. 2004). Breaking with bad habits, controlling emotions or resisting temptations are examples of self-control (Achtziger et al. 2015). Because of individual differences in self-control, it is conceptualised as a dispositional, trait-like construct that can be measured with questionnaires (Achtziger et al. 2015) e.g. the Brief Self-Control Scale by Tangney et al. (2004). The Brief Self-Control Scale has been used in over 60 studies (Maloney et al. 2012). In a recent study, Maloney et al. (2012) found out that the Brief Self-Control Scale consists of two distinct factors. Factor 1 is called 'Impulsivity' and factor 2 'Restraint'. Impulsivity is related to the tendency to acting out spontaneously on thoughts, feelings and external impulses. Restraint is related to self-control and the ability to resist temptation. Because the use of the self-control scale as an unidimensional scale can lead to construct contamination which can lead to an attenuation of the results (Maloney et al. 2012), we use the two factor design of the Brief Self Control Scale in our study. Furthermore, Maloney et al. (2012) demonstrate that the two-factor self-control scale shows desirable levels of reliability and discriminant validity.

Research Model and Hypothesis Development

Motivations to Start Self-Tracking

To account for different motivational factors, to start with different kinds of self-tracking activities, we clustered the most important parameters into three categories referring to the main categories of voluntary self-tracking (Verdezoto and Grönvall 2015): Physical parameters, medical parameters and parameters related to the general wellbeing of a consumer. We chose these three categories to account for parameters where restraint is of high relevance (physical parameters (Wills et al. 2007)), parameters which are in conflict with impulsivity (medical parameters (Wagner et al. 2016)) and parameters which are assumed to be neutral to self-control (wellbeing).

Previous studies found out that self-monitoring leads to increased self-awareness (Burke et al. 2009; Wilde and Garvin 2007). When people are in the state of self-awareness, they start to compare themselves to their standards (Selimbegović and Chatard 2013). If they do not come up to their own standards, people feel negative emotions and cognitive dissonance (Festinger 1962). Individuals try to match the discrepancy between the self and the standard, if they have a favourable outcome expectancy, but withdraw from a situation, if this is not the case (Duval et al. 1992). Some people are thereby confronted with more challenges as to self-monitoring than others, e.g. people who previously tried to achieve a goal and failed (Yu et al. 2015). Tangney et al. (2004) found a significant correlation between self-control and goal achievement. Some self-tracking parameters are thereby more controllable from an individual's perspective than others.

For example, sleeping quality is hardly influenced by the will power of a person but affected by environmental factors like noise and stress. A similar logic applies to parameters like sleep duration, mood and dreams which we assigned to the category wellbeing. Also the parameters blood pressure, blood test results, blood sugar, medication, symptoms and body water, which we subsume under the category medical parameters, cannot be fully influenced by people. Rennekamp et al. (2015) found out that people who are not responsible for an outcome experience no dissonance if they fail. In line with this result, we assume that people who track these parameters and do not reach their self-tracking goal will not experience strong negative emotions because they are not fully responsible for it.

In contrast, steps, climbed stairs, bicycle rides, running, workouts, endurance and muscle strength are parameters, which are directly influenced through behaviour. Therefore, we assume that not reaching the self-tracking goal in this category leads to cognitive dissonance.

Number of Tracked Parameters

Wills et al. (2007) found out that self-control in contrast to impulsivity is related to increased physical activity among adolescents. People with high levels of self-control are thus more likely to track these parameters because the likelihood to not reach the goal and experiencing negative emotions is smaller. This leads to our hypothesis that people with higher levels of restraint (self-control) are more likely to track physical parameters:

> *Hypothesis 1a: The level of restraint has a positive effect on the number of tracked parameters in the category physical.*

People who have high values of impulsivity appreciate immediate rewards more than delayed rewards (Daniel et al. 2013). They have the tendency to react rapidly and unplanned to internal or external stimuli without considering negative consequences (Moeller et al. 2001). Therefore, impulsivity is related to a multitude of unhealthy behaviour like drug use (Dougherty et al. 2004) and unhealthy eating (Lumley et al. 2016) which can lead to serious health related problems in the long run (Cecchini et al. 2010). Furthermore, Wagner et al. (2016) found out that medical compliance is much lower for people with higher level of impulsivity. If impulsive people focus on health related parameters, they supposedly feel dissonance because the impulsive behaviour is mostly not in line with this long term goal. We therefore assume that people with high values of impulsivity are less likely to invest in long term health related goals and are less likely to focus on health related parameters.

> *Hypothesis 1b: The level of impulsivity has a negative effect on the number of tracked parameters in the category medical.*

The category medical parameters include the factors blood pressure, blood test results, blood sugar, medication, symptoms and body water. According to Swan (2012) one of the main reasons individuals start self-tracking is to resolve issues and optimize a specific lifestyle. Therefore, we expect that health issues motivate users to track these parameters.

> *Hypothesis 2a: Starting with self-tracking because of health issues has a positive effect on the number of tracked parameters in the category medical.*

Wellbeing and health are related, but distinct dimensions, e.g. the quality of sleep (Paiva et al. 2015) and the mood (Heo et al. 2016) also have an influence on health. Therefore, health issues are also assumed to predict the number of tracked parameters in the category wellbeing, which consist of mood, feelings, general wellbeing, sleeping quality, sleep duration and dreams.

> *Hypothesis 2b: Starting with self-tracking because of health issues has a positive effect on the number of tracked parameters in the category wellbeing.*

Cheval et al. (2015) found out that physical activity intention leads to more physical activity. Thereby, they measured the physical activity from their participants through a three axis accelerometer on 7 consecutive days. In their investigation they also accounted for other mediation and moderation effects. Due to these results, we assume that the intention to improve personal performance has an influence on the willingness to track physical parameters because self-monitoring is easier with positive outcome expectancy. Therefore, we hypothesise:

> *Hypothesis 3: The intention to improve the personal performance has a positive effect on the number of tracked parameters in the category physical.*

Shin et al. (2015) found in a qualitative investigation that curiosity is a major motivational factor for using self-tracking tools. Therefore, we assume that curiosity plays a significant role in the decision to start with tracking activities. We expect thereby that curiosity has an influence on the tracking of all parameters because users who start out of curiosity are likely to try different software, sensors and functionalities of self-tracking tools.

> *Hypothesis 4 a-c: Starting with self-tracking because of curiosity positively affects the number of tracked parameters in the categories: (a) Medical, b) Physical and c) Wellbeing.*

Utilization & Value

Furthermore, it is straight-forward to assume that the more parameters are tracked (per group) the higher the usage frequency of self-tracking technologies.

> *Hypothesis 5 a-c: The number of tracked parameters in the category (a) Medical, b) Physical and c) Wellbeing has a positive effect on the usage frequency of self-tracking technologies.*

Expenditures in our context are measured by the accumulated money spend for all self-tracking related products (software & hardware) up to the point of the survey. Therefore, we expect that the number of tracked parameters in all categories has a positive effect on the accumulated expenditures for self-tracking. Entry into the world of self-tracking is possible at no cost, e.g. with simple free mobile software solutions. Therefore, we assume that consumers first explore the value of self-tracking before increasing their expenditures to support their more demanding tracking habits with e.g. additional software subscriptions or additional hardware. For instance, self-tracking of physical activities can be started by using a Smartphone and can be complemented by pulse monitors and other wearable devices. Therefore, we expect that tracking more parameters in all categories is a good predictor for the accumulated amount of money spent on self-tracking technologies up to the point of our survey.

> *Hypothesis 6 a-c: The number of tracked a) medical, b) physical and c) wellbeing parameters has a positive effect on accumulated expenditures for self-tracking technologies.*

The perceived value of a product has been defined as the ratio of the perceived benefit of a product and the perceived cost to obtain it (Monroe 1990). An important component of the perceived benefit is the frequency with which consumers believe they will use a product (Tanner and Carlson 2009). Hamilton et al. (2011) suggest that consumers estimate the value of a product by considering the absolute expected usage frequency but also the relative expected usage frequency in comparison to other consumers. In an extensive investigation they showed that relative usage frequency of products has an influence on the willingness to pay. Therefore, we assume that self-trackers spend more money on self-tracking tools if they use the self-tracking tools more extensively.

> *Hypothesis 7: The usage frequency has a positive effect on expenditures for self-tracking hardware & software.*

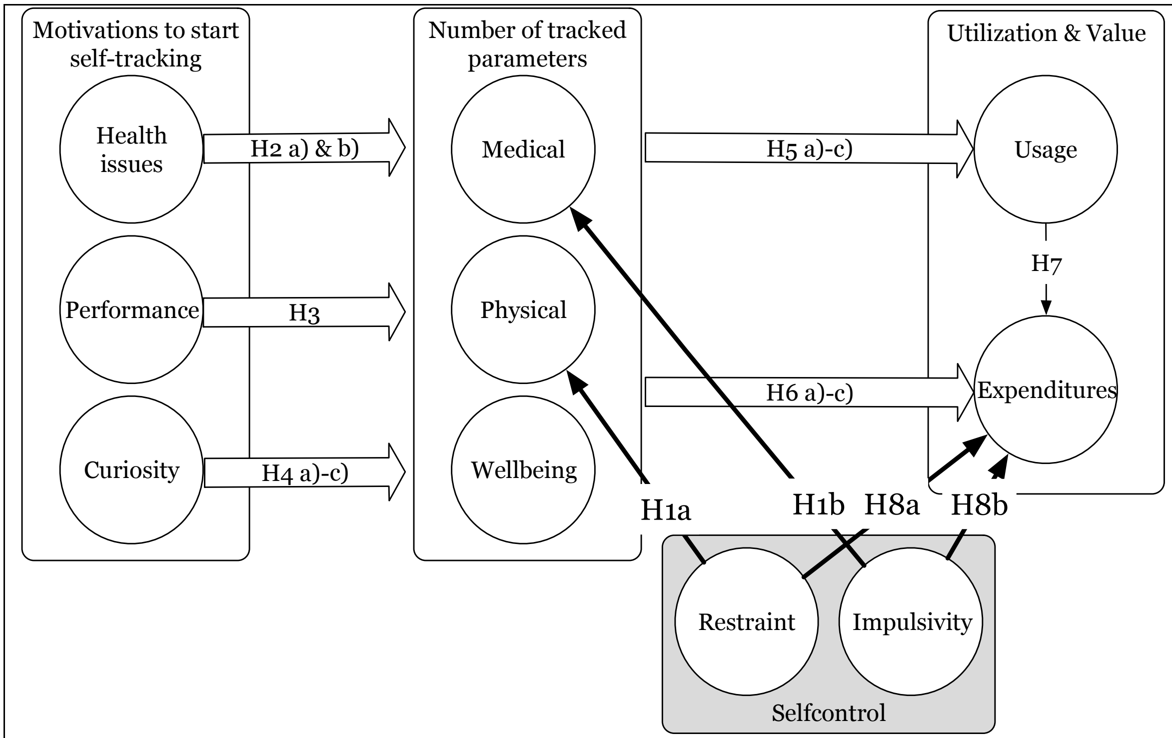
We expect that people which higher self-control, will reach their self-tracking goals more often whereby the mastery of goals is related to positive emotions (Goetz et al. 2015). In contrast, individuals with less self-control will fail to reach their self-tracking goals frequently and are confronted with cognitive dissonance and negative emotions. Furthermore, according to Duval et al. (1992), if an individual failed to reach a self-tracking goal, we expect that a person with a high level of restraint has, due to prior experience, a positive outcome expectancy as to reaching the goal and will therefore invest in achieving it, which in turn leads to positive emotions. Individuals with low levels of restraint are in contrast more likely to withdraw from any self-tracking activity. Consumers with a higher level of restraint are therefore more likely to reach their goal and therefore supporting technology generates a complimentary value. Therefore, we expect that the level of restraint predicts how much money people spend on self-tracking hardware and software.

> *Hypothesis 8a: The level of restraint has a positive effect on accumulated expenditures for self-tracking hardware and software.*

In contrast, we assume that impulsivity is negatively related to expenditure as regards self-tracking hardware and software. Impulsivity is related to rapid and unplanned behaviour without considering the negative consequences (Moeller et al. 2001). Therefore, we hypothesise that impulsive people feel more dissonance if they focus more on their behaviour through self-tracking. Therefore, we assume that people with high levels of impulsivity value self-tracking tools to a lesser extent.

> *Hypothesis 8b: The level of impulsivity has a negative effect on accumulated expenditures for self-tracking hardware and software.*

Figure 1 summarises our hypotheses.



Non-filled arrows symbolize groups of hypothesis. This stylized figure provides an overview of the essential model components. The complete model with all individual paths is reported in Figure 2.

Figure 1. Stylized Research Model

Research Method

Data Collection and Evaluation

We use a cross-sectional survey design to test our research model by using a convenience sample of users with self-tracking experience. The data was collected through a web-based survey that was implemented in the open-source software "LimeSurvey" and hosted on a university computer system. We ensured the anonymity of our participants by using appropriate privacy settings in the survey tool. The questionnaire was distributed via different social media channels in Germany, but was not specifically addressed to members of the Quantified-Self community. We are not interested in an analysis of the unique Quantified-Self community in particular because Shin et al. (2015) found out that participants of the Quantified Self group have different forms of motivation for using tracking devices. Our focus is instead the effect of self-control on average users. For that reason we focus on the self-tracking activities of consumers not associated with the Quantified Self movement. Our invitation to participate in the survey was followed by 245 participants, 130 of which completed the survey.

We consequently removed all participants from our sample that indicated to attend meetings of the Quantified Self community (n=8). We furthermore removed participants that indicated to have answered untruthfully or indicated in a control question to have never used any self-tracking technology at all (n=20). The remaining data set consists of 102 complete observations and was used for hypothesis testing

In the final sample, 54% of the respondents were female and the youngest (oldest) participant was 18 (48) years old while the average age was 26.24 (median=26, SD=5.51).

Measurement

For measuring self-control, we used the two-factor self-control scale based on Maloney et al. 2012. All items are surveyed via a five-point Likert scale ranging from "strongly disagree" to "strongly agree" and are presented randomly by the survey tool. The well-established self-control scale (Tangney et al. 2004) in its two-factor version was used without any modifications and fulfilled all reliability and validity criteria for multi-item scales in the study by Maloney et al. (2012). Nevertheless, to assess reliability in the context of our study we report composite reliability [CR] (Wertz et al. 1974) and consistency coefficient rho [CC] (Dijkstra and Henseler 2015) which should be both above 0.7 to demonstrate reliability of latent variables in our model. Both dimensions of self-control, 'restraint' (CR=0.81; CC=0.78) and 'impulsivity' (CR=0.77; CC=0.83) show desirable values of the aforementioned reliability coefficients. Following Henseler et al. (2015) we demonstrate discriminant validity by employing the heterotrait-monotrait ratio of correlations (HTMT), which is considered to be the most reliable measure in the context of PLS-SEM. Discriminant validity is established if the HTMT ratio of two constructs is below 0.90. In our study the HTMT ratio of correlations between restraint and impulsivity is 0.73.

Table 2.:Survey design and variables

Category		Variable	Description
Self-control (Tangney et al. 2004, Maloney et al. 2012) (5-point Likert) *Relation of items to Tangney's original self-control scale (S) in parenthesis.*	Restraint	R1 (S1)	I am good at resisting temptation.
		R2 (S2)	I have a hard time breaking bad habits. (R)
		R3 (S7)	I wish I had more self-discipline. (R)
		R4 (S8)	People would say, that I have iron self-discipline.
	Impulsivity	I1 (S5)	I do certain things that are bad for me, if they are fun.
		I2 (S6)	Pleasure and fun sometimes keep me from getting work done.
		I3 (S12)	Sometimes, I can't stop myself from doing something, even if I know it is wrong.
		I4 (S13)	I often act without thinking through all the alternatives.
Parameters tracked (Multiple choice)	Physical	P1-P8	Steps, climbed stairs, bicycle rides, running, workout, endurance, muscle strength and heart rate
	Medical	M1-M7	Blood pressure, blood test results, blood sugar, medication, symptoms and body water
	Wellbeing	W1-W5	Sleep quality, general well-being, sleep duration, mood and dreams
Motivations to start self-tracking (Binary choice)	Health	M1	I started with self-tracking because of health issues.
	Performance	M2	I started with self-tracking to improve my performance.
	Curiosity	M3	I started with self-tracking out of curiosity
Usage frequency (5-point Likert)		U	How often do you use self-tracking products (Hardware & Software)
Accumulated Expenditures (Open ended)		E	How much money have you spent on self-tracking technology (Hardware & Software) up to now in total?

Table 2. Survey design and variables

To ex-ante address a possible common method bias, we followed established guidelines in survey design. We mixed the order of questions and used different scale types to avoid a common method bias (Chang et al. 2010). However, we ex-post analysed our data for collinearity by inspecting the variance inflation factors (VIF) (Hair et al. 2014). The occurrence of VIFs greater than 5 is considered to be an indicator of a potential collinearity problem, and that a model may be contaminated by common method bias. However, VIFs in our model do not exceed the value of 1.53, indicating a common method bias is unlikely.

Furthermore, we survey the motives for starting to use self-tracking technologies (health related issues, performance increase, curiosity) via three binary choice questions. In the next step, participants could choose from a list of 20 different tracking parameters and indicate by multiple choice which parameters they track.

Binary coded variables are suitable in CB- and PLS-SEM analysis (Hair et al. 2012, Hair et al. 2014), as long as the respective variables are considered exogenous in the model specification. Furthermore, binary variables are used in acknowledged SEM studies by e.g. Han et al. (2015).

To isolate the effect of the two-factor self-control scale on the number of tracked parameters in different categories and on the expenditures for self-tracking technologies, we enriched our study by two additional control variables. The model includes the variables age and sex to account for demographic differences in our sample. Those control variables are not represented visually in the research model (Figure 1 & 2) but are included in the estimation and reported in Table 3. The effect of demographic differences is furthermore discussed in the following section.

Accumulated expenditures for self-tracking software and services were elicited via an open-ended question design (e.g. Miller et al. 2011). Participants were simply able to indicate how much money they spend in total (up to the point of the survey) for self-tracking related technologies by moving a slider. Table 2 summarises the variables and items in our study design.

Data Analysis and Results

In order to evaluate our model and test our hypothesis, we used the partial least squares method (PLS-SEM) (Ringle et al. 2005). Estimation was performed with the software application smartPLS 3.0. PLS-SEM is most appropriate in the early stage of a research effort or when the identification of possible relationships between constructs is more important than the magnitude of those relationships (Goodhue et al. 2012; Götz et al. 2010) as this is the case in the present investigation. To allow the reader to evaluate the explanatory power of our estimations, we report the R^2 for each dependent variable in Figure 2. The indicated values refer to the amount of explained variance of a dependent variable.

Number of Tracked Parameters

To test the influence of different motivational factors and self-control on the number of actually tracked parameters in different categories (H1-H4), we constructed three variables by aggregating the number of tracked parameters in each of the categories 'physical parameters', 'medical parameters' and 'wellbeing parameters' (c.f. Table 2).

We find support for hypothesis H1b as impulsivity has a significant negative effect on the number of tracked parameters belonging to the medical category. Impulsivity decreases the likelihood of tracking medical parameters, as participants with higher levels of impulsivity are more likely to feel dissonance because their impulsive behaviour is more likely not in line with their long term goals.

Furthermore, we find strong evidence to support hypotheses H2a & H2b as participants' health related issues have a significant positive effect on the number of tracked health related and wellbeing parameters. That result makes sense since wellbeing parameters, e.g. sleeping quality, are also relevant with respect to health-issues (Paiva et al. 2015).

Restraint (self-control) has a significant positive effect on the number of tracked parameters belonging to the physical category, which confirms hypothesis H1a. Restraint, as one factor of self-control, has a positive effect on the likelihood of tracking physical activities, as participants with higher levels of self-control are less likely to be frustrated by not achieving their personal fitness goals.

As expected, we also find support for hypothesis H3 as the intention to improve the personal performance has a significant positive effect on the number of tracked parameters belonging to the physical category.

In addition, we can confirm hypotheses H4b-H4c as curiosity has a significant positive effect on the number of tracked parameters in the categories physical and wellbeing. However, we have to reject hypothesis H4a, since there is no effect on the number of tracked medical parameters. In line with Shin et al. (2015), we are able to quantitatively support the argument that curiosity is one of the main driving forces for usual consumers to start self-tracking and track a wider variety of parameters. However, curiosity obviously does not affect the category of medical parameters. In contrast to parameters of the category wellbeing and physical, tracking of the parameters of the health category is most likely perceived as a necessity in case of health related issues rather than general interest to participants.

In general, we can conclude that the original reasons and motives for using self-tracking tools for specific purposes leads to a higher likelihood of using tools to track parameters in the respective categories. This result is indeed straight-forward. However, it helps us to disentangle the effect of self-control (restraint and impulsivity) from general self-tracking motives and usage intentions. In that sense the effects described in Hypotheses H2-4 work like control variables and support the robustness of the effect of restraint (self-control) on positively related parameters (physical) and the negative effect on parameters which are in conflict with impulsivity (medical).

Usage Frequency of Self-Tracking

In Hypotheses 5a)-5c), we proposed that a higher number of tracked parameters in each of the three parameter categories positively effecting the overall usage intensity of self-tracking technologies. However, we can only confirm hypotheses H5b and (weakly) H5c. The overall usage intensity of self-tracking technologies is therefore not significantly predicted by the number of tracked medical parameters. Therefore, one can conclude that in our sample the regular interaction with self-tracking technologies is predominantly driven by products for physical activities like fitness and sports and products related to wellbeing like sleep and mood tracking.

Accumulated Expenditures for Self-Tracking

In our sample respondents spent on average an accumulated 51.60€ (median=3.5€, 75%-percentile=53€, max=519€, SD= 98.81) on self-tracking related software, services & hardware up to the point of our survey. Two important aspects drive the descriptive statistics of expenditures in our sample. First, software for self-tracking is relatively cheap or even free of charge. The entry into the world of self-tracking (e.g. by mobile software) can be considered as costless. Self-tracking hardware is currently not widely adopted and has been purchased by only 38 (37.2%) of participants in our sample.

To explain the accumulated expenditures for self-tracking of participants our model includes self-control, as well as the number of tracked parameters in all aforementioned parameter groups, the overall usage intensity and both control variables to account for variations in demographic differences. That high level of control allows us to disentangle the possible effect of self-control from other drivers of expenditure as to self-tracking.

First, we can confirm Hypothesis H7 because usage frequency has a highly significant positive effect on the accumulated expenditures for self-tracking. Our results indicate furthermore that only the number of tracked parameters in the physical category has a strong significant positive direct effect on accumulated expenditures for self-tracking, which confirms hypothesis H5b.

The tracking of wellbeing parameters has only a small and weak indirect effect on expenditures for self-tracking via usage frequency (see Table 3), which delivers some support for hypothesis H5c. However, we have to reject hypothesis H5a, because there is neither a direct nor an indirect effect of the number of tracked medical parameters on the expenditures for self-tracking. Interestingly, many of the health related parameters (e.g. blood pressure, blood sugar, etc.) need specific hardware because the relevant parameters are not directly observable or measurable by software.

Table 3. PLS Estimation Results			
	Total Effects	**Direct Effects**	**Indirect Effects**
Age -> Medical	-0.031	-0,031	-
Age -> Physical	0.046	0,046	-
Age -> Usage	0.185+	0,162	0.023
Age -> Expenditures	0.268*	0,167*	0.101+
Age -> Wellbeing	0.058	0,058	-
Curiosity -> Medical	0.106	0.106	-
Curiosity -> Physical	0.294***	0.294***	-
Curiosity -> Usage	0.136**	-	0.136**
Curiosity -> Expenditures	0.132**	-	0.132**
Curiosity -> Wellbeing	0.232**	0.232**	-
Gender -> Medical	0.099	0.099	-
Gender -> Physical	-0.167*	-0.167*	-
Gender -> Usage	0.08	0.118	-0.038
Gender -> Expenditures	0.047	0.044	0.003
Gender -> Wellbeing	0.027	0.027	-
Impulsivity -> Medical	-0.293*	-0.293*	-
Impulsivity -> Usage	-0.015	-	-0.015
Impulsivity -> Expenditures	0.123	0.132	-0.009
Medical -> Usage	0.053	0.053	-
Medical -> Expenditures	0.029	0.003	0.026
Performance -> Physical	0.364***	0.364***	-
Performance -> Usage	0.105*	-	0.105*
Performance -> Expenditures	0.131**	-	0.131**
Physical -> Usage	0.29**	0.29**	-
Physical -> Expenditures	0.36***	0.218**	0.142*
Restraint -> Physical	0.202*	0.202*	-
Restraint -> Usage	0.059	-	0.059
Restraint -> Expenditures	0.318**	0.245*	0.073+
Health -> Medical	0.337*	0.337*	-
Health -> Usage	0.07	-	0.07
Health -> Expenditures	0.037	-	0.037
Health -> Wellbeing	0.266*	0.266*	-
Usage -> Expenditures	0.49***	0.49***	-
Wellbeing -> Usage	0.195+	0.195+	-
Wellbeing -> Expenditures	0.101	0.005	0.095+

(T-statistics in parentheses; + $p<0.10$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$)

Table 3. PLS Estimation Results

Nevertheless, most of those costs are reimbursed (or paid directly) by insurance companies in Germany. Therefore, that effect may be driven by the fact that costs of health related self-tracking activities are likely not burdened by the customers themselves, but rather by third parties in the healthcare system.

Inspection of the results with respect to self-control shows a significant positive effect of restraint on the expenditures for self-tracking, but no significant effect of impulsivity. Thereby we can confirm hypothesis H8a but have to reject hypothesis H8b. That result indicates that self-tracking hardware is perceived as more valuable by restraint (self-controlled) consumers which are more likely to assume to reach their goals than other consumers. That result again supports the argument that self-tracking is more valued by customers that already show high levels of self-control, rather than customers that would profit from additional insights about themselves and more self-monitoring capabilities.

Besides the impact of self-control, we find an additional effect by inspecting our control variables. Age has a significant positive effect on the expenditures for self-tracking technologies, which might be driven by a higher income of older respondents compared to younger participants in our sample.

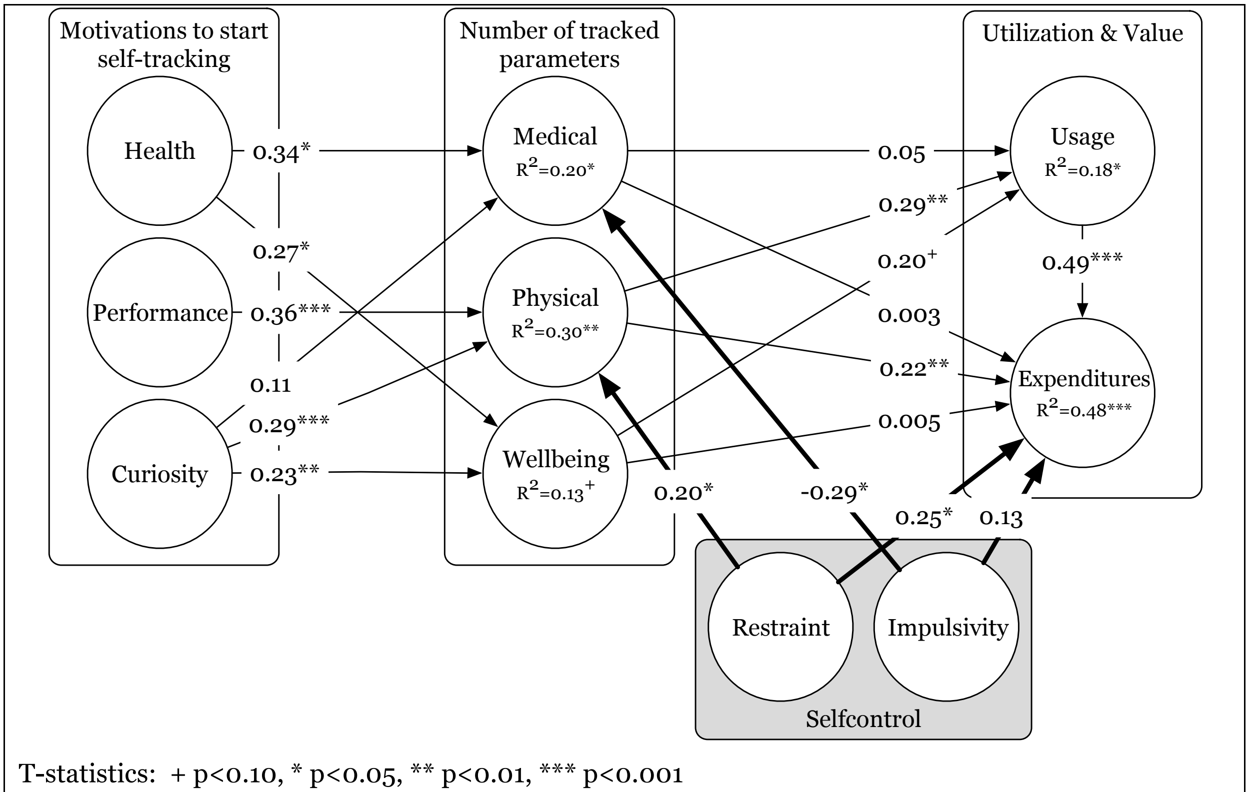


Figure 2. Model Results: Direct Effects

Indirect Effects

We report indirect effects via the number of tracked parameters in each category on usage frequency, as well as indirect effects on accumulated expenditures via usage frequency of self-tracking.

We find that tracking of wellbeing parameters has only a small and weakly significant indirect effect on expenditures for self-tracking via usage frequency, but we observe a significant positive indirect effect of curiosity on the expenditures for self-tracking. Therefore, some revenue generated by self-tracking products is implicitly driven by curiosity of customers and not a specific purpose of the technology itself. Furthermore, we find significant indirect effects of performance motivations to start self-tracking on usage frequency and accumulated expenditures for self-tracking, implying that performance motivations implicitly drive revenue of self-tracking products as well.

Discussion and Conclusion

Our study addresses the questions how different motivations to start self-tracking drive the actual tracking activates of users and how self-control affects the tracking of specific parameter categories and the amount of money that is spent by normal self-tracking consumers not actively involved in the unique Quantified Self community. We investigate how self-tracking motivations, especially curiosity, which has been assumed to be the main driver of normal consumers self-tracking activity, affects the number of tracked parameters in three different parameter categories, of which two are assumed to be affected by the level of self-control as well. To this end, we analysed data from 130 consumers, gathered via an online-questionnaire.

First, we find that restraint (self-control) has a significant positive effect on the likelihood of tracking physical parameters and the expenditure as regards self-tracking, but we could not confirm that people with higher levels of impulsivity spend less money for self-tracking tools. Based on these findings we conclude that self-tracking is of more value to consumers that already show a higher level of restraint because they are more likely to reach their goal and are confronted with more positive self-tracking results. Due to impulse buys it is possible that some people with high levels of impulsivity also buy additional self-tracking tools even if they have made the experience that negative self-tracking results frustrate them. Furthermore, we find support for our hypothesis that impulsivity has a negative effect on the likelihood of tracking parameters from the medical category. These findings have important implications for e.g. insurance companies that try to motivate their customers to use self-tracking tools because people with a higher need for such technologies (higher levels of impulsivity) are less likely to spend money for such tools or use them to track medical parameters.

Second, performance motivations and the number of tracked physical parameters are a strong driver of usage frequency and accumulated expenditures. Those motivations and tracking activities directly and indirectly influence usage frequency and aggregated expenditures, as demonstrated in the previous section. Part of the value of self-tracking is therefore directly and indirectly related to self-tracking software, services & hardware supporting users with the motivation to increase their performance and to achieve their fitness goals.

Third, customers that started self-tracking out of pure curiosity spend significantly more on self-tracking software, services & hardware and are at the same time more likely to track parameters from a wider variety of categories. Curiosity, as one main driving force to enter the world of self-tracking should be fostered by service providers to direct users with lower levels of self-control to functions helping them to foster active and long-term self-monitoring behaviour. Features that those customers otherwise may not have actively requested and discovered. Users starting out of curiosity are most likely not sure about the future value of self-tracking and have to identify parameters and software features relevant to them first. In addition to that, usage frequency, not the amount of tracked parameters, is the mayor driving force of consumer expenditures. Therefore, even very specialized self-tracking products can generate value by implementing features focusing on regular and repeated interaction with their customers.

Future research in the field of information systems should address the question of how self-tracking services can be designed to successfully create value for people with lower values of self-control and to encourage them to exert desirable and healthy levels of activity.

Limitations

It is important to evaluate the results of our study under the consideration of several limitations. Our data was collected from a convenient sample from Germany and the sample size was rather small. Furthermore, we cannot fully exclude a possible common method bias, because our study fully relies on self-reported online-questionnaire data. Furthermore, future research should address the questions whether cultural differences influence self-tracking behaviour and whether self-control has an effect on the continuance of self-tracking activities. In addition, future studies should also take into account fashion and social status considerations of consumers when purchasing self-tracking products.

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