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## **A Quantum of Self: A Study on Self-Quantification and Self-Disclosure**

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### **Highlights**

- The paper explores the phenomenon of self-quantification in the context of self-tracking devices and mobile applications.
- Self-quantification is associated with emotional stability and conscientiousness.
- More frequent self-quantifiers will be more likely to disclose personal information.
- Privacy concerns and institution-based trust do not affect information disclosure.

### **Abstract**

More and more people track themselves with gadgets and apps such as Fitbit, Endomondo, and MoodPanda etc. Such apps promise more organized lifestyles. However, some of the tracked tracked can be sensitive. Thus, users make themselves vulnerable and face the risks of privacy invasions. So far, few studies have empirically investigated issues of privacy and self-disclosure in self-tracking. Based on the privacy and self-disclosure literature, we conduct a survey of 475 individuals. First, we explore the psychological antecedents of self-quantification and then evaluate the effect of self-quantification on self-disclosure. We find a significant effect of self-quantification on self-disclosure in the survey context, indicating that individuals who habitually use self-trackers are also more likely to disclose personal data in other contexts.

**Keywords:** self-tracking, quantified self, privacy, self-disclosure, mobile media

## **A Quantum of Self: A Study on Self-Quantification and Self-Disclosure**

### **Introduction**

The market for wearable technologies (Apple Watch, Fitbit etc.) and self-tracking applications (Endomondo, MyFitnessPal, MoodPanda etc.) is growing rapidly. Forecasts predict that up to 245 million units will be sold in 2019, compared to the 84 million devices sold in 2015 (CCS Insight, 2016). Wearable technologies and self-tracking applications do not only allow users to monitor their health data but document various aspects of their lives, enriching their experiences with instant feedback. Wearable cameras such as “GoPro” record film based on what individuals see during the day. Augmented reality headsets such as “KANO” adapt sound to someone’s bodily needs and environmental noise. Applications such as “Nipple” even allow users to record sexual activities and to compare their performance to the global average. These examples demonstrate the ease of obtaining rich data about individuals’ performance, of examining these data, and of acting on it. This process is referred to as self-quantification (Li, Dey, & Forlizzi, 2010; Lupton, 2013a).

An important implication of self-quantification lies in the disclosure of personal information. The data collected through self-tracking is available not only to users but also to companies which offer self-tracking services, as well as to third parties who cooperate with the service-provider. As a result, personal and at times sensitive information about health, finances, social interactions, diet, and sexual activities, which was previously only shared with a doctor or a close circle of trustees, becomes available to service-providers and various analytics and advertising agencies. Thus, self-quantification comes with considerable privacy implications. However, research has only started to explore privacy in the context of self-quantification. We lack systematic empirical evidence about how much individuals involved in self-tracking care about their personal privacy and whether the privacy paradox (Kokolakis, 2017) exists in this context. Such knowledge can benefit theory and practice. The theoretical relevance lies in

informing current debates in Internet research, for example about post-privacy (Burkart & Andersson Schwarz, 2014), datafication (Van Dijck, 2013), selfhood (Lupton, 2016), passive participation, (Lutz & Hoffmann, 2017), and agency in big data and data mining (Kennedy & Moss, 2015). In practical terms, the findings point to the importance of data protection, both among the users and providers of quantified-self solutions. This contribution provides insights into the privacy-self-quantification nexus by systematically assessing how privacy, self-disclosure, and psychological characteristics are interrelated among self-quantifiers.

Accordingly, the central *research questions* of this paper are: *What is the psychological profile of frequent users of self-tracking applications? Does more frequent use of wearable technologies and self-tracking applications result in the disclosure of more personal information in other contexts?* To answer these questions, we analyze empirical data collected in 2016 with structural equation modelling.

## **Literature Review**

### **Self-quantification**

The term “quantified-self” was first introduced in 2007 to refer to individuals who are interested in the automation of data collection (Lee, 2013). Almost a decade after the term first emerged, scholars have now studied the process of self-quantification across the fields of communication, marketing, human-computer interaction, and sociology. Because self-quantification is such a recent concept in the academic literature, there is no institutionalized definition. Depending on the research field, “self-quantification” is often used as a synonym for “personal informatics” (Li et al., 2010), “self-surveillance” (Lupton, 2016), “self-tracking” (Neff, 2016), “self-monitoring” (Lupton, 2013a), “life-logging” (Rettberg, 2016), “personal analytics” (Choe, Lee, Lee, Pratt, & Kientz, 2014), and “self-measuring” (Etkin, 2016).

Even though the term “self-quantification” was introduced only a decade ago, the activities of collecting and interpreting data on one’s own thoughts and behaviors are not new.

For sixty years, Benjamin Franklin recorded whether he lived his days according to thirteen set virtues on a daily basis (Neff, 2016). Buckminster Fuller had a scrapbook where he recorded every fifteen minutes of his life (Li et al., 2010). Personal diaries (both handwritten and digital) and photo albums have served as tools for life-logging and can thus also be considered as a form of self-quantification (Rettberg, 2016). The main difference between engaging in self-quantification now and a decade ago lies in the technological advancement of self-tracking tools. Self-tracking mobile applications and wearable technologies now allow data to be collected instantly and with minimal effort. Moreover, the ease of data interpretation has also increased due to customized feedback systems, the enhanced user-friendliness of interfaces, and sophisticated visualization techniques employed in applications and wearables.

Self-quantification is a process of collecting and interpreting data on various life practices (Lupton, 2013a) and can be viewed as an outcome of self-tracking. Self-tracking is the activity of recording, capturing, indexing, and analyzing personal data using experiential computing devices such as mobile applications and wearable technologies (Sjöklint, 2014). In this paper, we define self-quantification as the process of collecting and reflecting on personal data by using wearable technologies and self-tracking applications.

Current research shows that self-quantification is a process consisting of several stages (Choe et al., 2014; Marcengo & Rapp, 2014; Sjöklint, 2014): data collection, visual representation of data, cross-linking of data to discover correlations, gaining insights, and acting upon insights. A stage-based model of personal informatics systems incorporates all the stages mentioned above (Li et al., 2010). Personal informatics systems are defined as “those that help people collect personally relevant information for the purpose of self-reflection and gaining self-knowledge” (Li et al., 2010, p. 588). The author of the definition highlights that “personal informatics” and self-quantification can be used interchangeably. Therefore, we use a stage-based model to operationalize self-quantification in this paper. We consider the

following phases: “preparation”, “collection”, “integration”, “reflection”, and “action.” An individual undergoes these five iterative stages in a process of self-quantification.

The first stage, preparation, describes an individual’s motivations to collect personal information. Individuals track their performance for various reasons. The study of extreme self-quantifiers reveals that the main motivation for self-quantification is the achievement progress, in the sense of improvement or performance optimization (Choe et al., 2014; Swan, 2012, 2013). Other important reasons for self-quantification are: natural curiosity, an interest in data, reminiscing about the past, and aiding memory (Li, Dey, & Forlizzi, 2011).

The second stage in the self-quantification process is concerned with data collection. Self-quantification occurs across the contexts of physical and emotional health (e.g., sleep quality tracking, weight loss, work out planning, mindfulness), work (e.g., productivity improvement), and hedonic experiences (e.g., travelling) (Choe et al., 2014; Swan, 2013). Since individuals have various motivations and contexts for engaging in self-quantification, individuals collect different types of data. Most commonly, individuals self-track physiological states such as body temperature, heart rate, or breathing patterns. Some individuals also measure their states of mind (e.g., mood, energy levels, thinking patterns), their location (e.g., destinations visited), timings (e.g., performance time intervals), and the people they interact with (Marcengo & Rapp, 2014). Data can be acquired through direct self-measuring by using wearable technologies or sensors, through inferences (e.g., using algorithms to derive final data), or through self-reporting such as manual data entry (Marcengo & Rapp, 2014).

As soon as the data is collected, either an application or the user prepares, combines, and transforms the data for further analysis. This stage of making data ready for further reflections is called “integration” (Li et al., 2010).

During the next two stages of “reflection” and “action”, individuals make sense of the collected data, reflect on the insights they received, and adjust their behavior accordingly.

Importantly, the stages of self-quantification are iterative. Individuals may not go through all the stages every time they engage in self-quantification and the stages may occur simultaneously. For example, an application may generate instant performance feedback and individuals may adjust their behavior directly, skipping “integration” and “reflection”.

Given the newness of the topic, few studies have investigated self-quantification empirically. Most existing research is qualitative and exploratory. In the domain of human computer interaction, for example, Choe et al. (2014) used an ethnographic approach to study the self-quantification experiences, data collection practices, and motivations for self-quantification of users on the platform *quantifiedself.com*. Their study analyzed the videos of 52 users. Another study focused on motivations to engage with self-tracking devices and applications, and barriers that negatively affected engagement among 68 users (Li et al., 2010).

Sociological perspectives on self-quantification are represented by research on the cultural, societal, and ethical implications of self-quantification. Lupton (2015) performed a content analysis of mobile applications that track sexual activities and functions. She discovered that using such applications leads to perpetuating stereotypes about sexuality. Another study focused on self-tracking modes in order to investigate how individuals engage in self-quantification (Lupton, 2016).

Recent studies have mainly adopted qualitative approaches to studying motivations, experiences, and the implications of self-quantification (e.g., Lomborg & Frandsen, 2016). However, only minimal quantitative evidence on the topic exists and we thus know little about the overall prevalence of self-quantification.

Regarding outcomes, questions of how self-quantification affects personal wellbeing, social capital, a sense of intimacy and privacy, and other attitudinal and behavioral factors remain largely unanswered. As an exception, Etkin’s (2016) study on self-quantification in consumer research proposes mechanisms through which self-quantification might affect



performance and satisfaction. The findings suggest that self-measuring has a positive effect on performance but a negative effect on satisfaction with the associated activity. When tracking reading and drawing speed and counting steps, self-measurement undermines intrinsic motivation and fuels extrinsic motivation (Etkin, 2016). Individuals in the self-measurement condition performed better but enjoyed the activity less because they were more focused on the performance output than on the activity itself. A possible explanation for such a relation is that supposedly pleasurable activities seemed like work.

To sum up, the existing literature on self-quantification mainly focuses on the motivations, contexts of engagement with self-quantification, and the engagement experience itself. However, there is no established literature on the personality traits of self-quantifiers. In addition, behavioral outcomes of self-quantification are sparsely covered in the existing research. This study aims to address both gaps by providing insights into traits associated with self-quantification and self-disclosure as a behavioral outcome of self-quantification.

### **Self-quantification and personality traits**

The first step is to investigate how personality traits affect self-quantification. To do so, we connect personality traits to self-quantification by implementing the five factor model (John & Srivastava, 1999). The five factor model includes five personality traits as descriptors of personality: extraversion, agreeableness, conscientiousness, emotional stability, and openness to new experience (Barrick & Mount, 1991). As previously outlined, individuals engage in self-quantification for reasons such as performance optimization, natural curiosity, data interest, and reminiscence about the past. As for the contexts of self-quantification, the most common domains are: health and wellness, hedonic experiences, and the workplace. We believe that linking motivations and self-quantification contexts to personality traits can be a first step in investigating the complexity of self-quantification.

Based on research by John and Srivastava (1999), Gosling et al. (2003), and Barrick and Mount (1991), we will briefly outline traits associated with each factor. Extraversion is associated with talkativeness, assertiveness, industriousness, and enthusiasm. Agreeableness is measured by the extent to which an individual is sympathetic, forgiving, cooperative, and trustful. Conscientiousness is associated with being self-disciplined, organized, dependable, and responsible. Traits such as calmness, absence of neuroticism, and anxiety are related to emotional stability. Finally, being imaginative, curious, and original is related to being open to new experiences.

Collecting and recording data are essential stages of the self-quantification process. Data collection for the purpose of self-quantification requires a certain level of organization, order, or discipline (Li et al., 2010). A vivid example of such organization and discipline is a two-year project on food consumption completed by Lauren Manning (2010). She tracked her food consumption during two years and documented it by creating and analyzing different visual representations. Since data collection requires organization, planning, and discipline, we expect conscientiousness to be positively associated with self-quantification.

**H1:** *Conscientiousness has a positive effect on self-quantification.*

Natural curiosity (Li et al., 2010; Whooley, Ploderer, & Gray, 2014) and the search of new experiences in life (Choe et al., 2014) are among the key motivations for self-quantification. People are curious about how their minds and body work and whether their visualized data has patterns (Whooley, Ploderer, & Gray, 2014). Openness to new experiences is associated with curiosity (Choe et al., 2014). We therefore expect openness to new experiences to have a positive effect on self-quantification.

**H2:** *Openness to new experiences has a positive effect on self-quantification.*

Self-quantification is frequently discussed within the healthcare literature (Lomborg, & Frandsen, 2016). Health and wellbeing are the most common contexts for self-quantification

(Fox & Duggan, 2013). While 19 percent of US adults without chronic conditions report tracking health indicators or symptoms, almost two thirds (62 percent) with 2+ conditions do so (Fox & Duggan, 2013). These findings relate mostly to physical health conditions, such as high blood pressure or diabetes, but we would argue that mental health issues might also encourage a desire for self-tracking in order to improve the condition. We therefore expect people with both physical and mental health problems to be more prone to self-quantification. Emotional stability is associated with an important aspect of health, namely mental health. Thus, emotional stability should result in lower levels of self-quantification.

**H3:** *Emotional stability has a negative effect on self-quantification.*

Self-quantification depends on the level of trust in the technology, because, in order to engage in self-quantification, individuals first have to provide a technology with access to their data. Second, they have to rely on the output information of a wearable device or application (Ruckenstein, 2014). Additionally, the environment in which self-quantifiers share and discuss their data is described as an “environment of trust” (Swan, 2013). Trust, is one of the facets of agreeableness and we therefore expect agreeableness to have a positive effect on self-quantification.

**H4:** *Agreeableness has a positive effect on self-quantification.*

According to Lomborg and Frandsen (2016), recording and analyzing data on one’s behavior is fundamentally communicative. They take a communication perspective on the phenomenon of self-tracking and argue that self-tracking should be conceptualized in terms of communication along three dimensions: communication with a digital system, communication with self, and communication with peers. Because self-tracking is an inherent part of self-quantification, such a communication perspective can be applied to self-quantification. From this perspective, using wearable technologies to measure is a way of “speaking” to different agents (self, community, and digital system) by means of data. Therefore, extraversion, which

is associated with talkativeness, should have a positive effect and extraverted individuals should be more likely to use data to communicate about themselves.

**H5:** *Extraversion has a positive effect on self-quantification.*

Constant exposure to tracking may lead to a more pragmatic attitude to privacy among self-quantifiers and, having fewer privacy concerns, may in turn affect disclosure. To establish the link between self-quantification, self-disclosure, and privacy we will now discuss key research on self-disclosure and online privacy.

### **Self-quantification and self-disclosure**

When using online services, Internet users typically leave traces. This can be consciously, for example through filling out an online form and providing profile information, or unconsciously, through browsing websites. The process of leaving such traces is called self-disclosure. In a classical, more systematic definition (pre-Internet), self-disclosure was conceptualized as “*any message about the self that a person communicates to another*” (Wheless & Grotz, 1976, p. 47). We follow this definition in this article and are interested in both intentional and unintentional self-disclosure.

The literature on self-disclosure is strongly inspired by social exchange theory (Homans, 1958) and the idea that users weigh the benefits of disclosure against the costs (Krasnova, Spiekermann, Koroleva, & Hildebrand, 2010). Sharing personal information can be associated with certain benefits. For example, disclosing more information about socio-demographic characteristics may improve the accuracy of feedback from health and wellness applications. In qualitative studies of self-quantification, self-quantification is often associated with a certain lifestyle characterized by technological optimism and positivism. One of the examples of such technological optimism is the attitude of self-quantifiers to data generated by wearables and self-tracking apps. Such data is perceived as more objective, neutral (Lupton, 2013a), and scientific (Lupton, 2013b) than human judgements and perceptions. Due to

perceived properties of data (neutrality and unbiasedness), information which users receive from self-tracking technologies seems credible and trustworthy.<sup>1</sup> Self-quantifiers are more data-minded and therefore disclosing personal information may seem to serve as a prerequisite for a better service.

In addition, research in human-computer interaction suggests that people who track their performances see their data as a contribution to collective value projects (Ruckenstein, 2014). Specifically, data production through self-quantification may give self-trackers access to information about bodies and minds that people have previously been unaware of (Thrift, 2011). In a recent study on the official community “Quantified-Self”, Barta and Neff (2016) explore the value orientations of the community. They argue that the “Quantified-Self” community is an example of a sharing economy institution, where people share their knowledge in order to help others make sense of their data.

This leads us to theorize that self-quantifiers are inherently motivated to disclose personal information, because they value data sharing for themselves and for the community, and because it has become a habit. Thus, users who are more engaged in self-tracking activities develop a more pragmatic approach towards self-disclosure, leading to a lessened sense of perceived information sensitivity and heightened self-disclosure. Therefore, self-quantification should be positively associated with self-disclosure.

**H6:** *Self-quantification has a positive effect on self-disclosure.*

### **The role of privacy concerns and institution-based trust**

Privacy is a multi-disciplinary research field and disciplines involved in its study include (among others) communication, computer science, psychology, sociology, and law (Pavlou, 2012). Researchers have repeatedly alluded to the multi-dimensionality of privacy

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<sup>1</sup> Not only for users but also for researchers, data from self-tracking technologies offers distinct benefits and qualities because it avoids biases inherent in self-reported data. Such considerations have been brought up in the literature about “ecological momentary assessment” (Shiffman, Stone, & Hufford, 2008).

(Smith, Dinev, & Xu, 2011), with the central phenomenon being difficult to define. As Solove (2008, p. 1) points out: “*Currently, privacy is a sweeping concept, encompassing (among other things) freedom of thought, control over one’s body, solitude in one’s home, control over personal information, freedom from surveillance, protection of one’s reputation, and protection from searches and interrogations. Philosophers, legal theorists, and jurists have frequently lamented the great difficulty in reaching a satisfying conception of privacy.*”

In this article, we are interested in informational privacy (Solove’s “control over personal information” point) rather than physical privacy or other forms mentioned above. In the informational context, privacy concerns have been of great interest over the last decade. Some scholars have pointed out that current Internet applications, such as social media, are associated with a puzzling variety of privacy threats, resulting in privacy concerns (Dienlin & Trepte, 2015). Accordingly, many empirical studies have shown that a large proportion of Internet users are concerned about their online privacy (for descriptive studies, see Eurobarometer, 2015; Madden & Rainie, 2015). However, in many cases, privacy concerns do not result in corresponding privacy protection behavior or reduced self-disclosure. The divergence between online privacy attitudes and behavior has been termed the “privacy paradox” (Barnes, 2006). As of today, a substantial number of studies exist on the phenomenon, with mixed empirical evidence and a range of theoretical approaches (cf. Kokolakis, 2017 for an overview). “*Research on the privacy paradox has followed a dialectic course. Initial studies that revealed a dichotomy between privacy attitude and actual privacy behavior were followed by others that showed a significant influence of privacy attitude on privacy behavior*” (p. 130). Accordingly, we propose that greater levels of privacy concerns should result in less self-disclosure.

**H7:** *Privacy concerns have a negative effect on self-disclosure.*

Given scarce research, we have no systematic evidence for how privacy concerns affect engagement with self-quantification behavior. However, we propose that such behavior is curbed by privacy concerns due to the often very sensitive nature of the data collected through self-tracking and the inherent privacy risks.

**H8:** *Privacy concerns have a negative effect on self-quantification.*

The information systems and marketing literature frequently conceptualize privacy and privacy concerns as a barrier to forming trust, and privacy protection guarantees as a means of establishing trust (e.g., Bart, Shankar, Sultan, & Urban, 2005; Beldad, De Jong, & Steehouder, 2010; Hoffmann, Lutz, & Meckel, 2014). Accordingly, most studies find a significant negative effect of privacy concerns on online trust (e.g., Chen & Barnes, 2007). This leads us to formulate the following hypothesis.

**H9:** *Privacy concerns result in lower levels of institution-based trust.*

The calculus perspective of conscious actors weighing the benefits of disclosure against the privacy risks is one of the key explanations for the privacy paradox (Dinev & Hart, 2006). Next to the privacy calculus approach (e.g., Lee, Park, and Kim, 2013), a second theoretical approach focuses on user trust, that is “*a psychological state comprising the intention to accept vulnerability based upon positive expectations of the intentions or behaviors of another*” (Rousseu, Sitkin, Burt, & Camerer, 1998, p. 395). In this view, users form generalized and heuristic expectations towards transaction partners rather than considering and evaluating the risks and benefits of online transactions (McKnight, Choudhury, & Kacmar, 2002). Such expectations allow for a more carefree reliance on the trustee. This approach complements the privacy calculus-perspective by considering both cognitive and affective motives for online self-disclosure (Krasnova et al., 2010). Nonetheless, while trust represents a key prerequisite for the establishment and growth of online services, there is little evidence that users trust those

services which they disclose personal information to, such as SNS (Klara, 2016; Young & Quan-Haase, 2013), whereas trust in the Internet has a positive effect on self-disclosure.

**H10:** *Institution-based trust has a positive effect on self-disclosure.*

Similar to the connection between privacy concerns and self-quantification, the nexus between trust and self-quantification is understudied. However, given extensive research in other contexts (e.g., McKnight et al., 2002), we propose that trust – both in a specific service and in the general infrastructure of the Internet – acts as a positive antecedent of behavior, in this case self-tracking.

**H11:** *Institution-based trust has a positive effect on self-quantification.*

Finally, we include perceived information sensitivity as a control variable for self-disclosure. Users of wearables and self-tracking applications collect different types of data and research has shown substantial variation in what data is considered sensitive (Madden, 2014). In the US, for example, social security numbers and health states are considered particularly sensitive, while purchasing habits are not considered to be very sensitive (Madden, 2014). Likewise, how sensitive individuals perceive various data types to be will likely affect their self-disclosure.

**H12:** *Perceived information sensitivity has a negative effect on self-disclosure.*

Figure 1 shows the research model investigated in this paper.

INCLUDE FIGURE 1. “RESEARCH MODEL” HERE

## **Methodology**

### **Survey description**

To investigate the relationship between personality traits, self-quantification, and self-disclosure, we conducted an online survey through Amazon Mechanical Turk (AMT). The survey administration was handled through TurkPrime and 475 individuals filled out the



questionnaire. The survey was programmed in Qualtrics, with the link being posted on AMT in mid-October 2016. In the introductory text, we stated that this survey was targeted at users of wearable technology and self-tracking apps.<sup>2</sup> Within 24 hours, a sufficient number of participants had filled out the survey. The questionnaire consisted of a series of open and closed questions. In the open questions, participants were queried about personal information on a spectrum from less sensitive to more sensitive personal information. Except for some demographic questions, the remainder of the survey consisted of closed questions where respondents could state their agreement to a statement on a five-point Likert scale, ranging from 1-strongly disagree to 5-strongly agree, with somewhat disagree, neither agree nor disagree, and somewhat agree as the middle categories. A sample item was *“All things considered, the Internet could cause serious privacy problems.”* More information for specific scales can be found in the next section.

The survey took slightly less than 10 minutes to fill out (average number of seconds = 550; median number = 439). The respondents received a monetary reward of 1.5 US Dollars with an additional 0.5 US Dollar bonus for completion.

We included an attention check question in the middle of the survey, with the wording, *“The purpose of this question is to assess your attentiveness to question wording. For this question, please mark the ‘Somewhat disagree’ option.”* 24 participants (5.1 percent) failed the attention check and were excluded from the data analysis. This left us with a sample of 451 respondents, 410 of which entered the structural equation model (SEM). 41 respondents had missing values for at least one of the items used in the SEM and many of these – 14 in number – resulted from missing values on the self-disclosure and information sensitivity questions (see section “Self-disclosure measure”).

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<sup>2</sup> The first paragraph of the survey introduction was: “In the following survey, we are interested in your opinions about wearable technologies such as Fitbit and Apple Watch. We are also interested in self-tracking via mobile apps such as Endomondo, Runtastic or MyFitnessPal.”

52.4 percent of respondents were male, 47.4 percent were female, and one person (0.2 percent) identified as other. The average age in the sample was 33.3 years old and the median was 31 years old (standard deviation 9.17 years, with a range of 52 years from 18-70 years). In terms of education, 25 percent of all respondents had some college education, 40 percent had a 4 year bachelor's degree, 7 percent had a master's degree, and 13 percent had a 2 year bachelor's degree. On the lower end of the spectrum, 12 percent had a high school diploma as their highest qualification and 3 people (0.6 percent) had less than a high school degree. On the higher end, 2 percent had a doctorate or professional degree (JD, MD). Thus, the sample included a broad range of educational backgrounds.

### **Self-quantification measures**

We loosely relied on a stage-based model of personal informatics systems (Li et al., 2010) for measuring self-quantification. Based on the stages of self-quantifiers, we developed a set of 15 items to assess how individuals collect, analyze, and reflect upon data. Respondents were asked to state their agreement on a 5-point Likert scale. Initial principal component analysis of all 15 items showed low loadings on three items related to attitudes towards collected data. Therefore, we excluded those three items from the analysis. The remaining twelve items relate to data collection (importance and frequency of data collection), reflection (data monitoring, analysis, comparison, pattern recognition), and action upon data (decision-making and behavioral adjustment). All twelve items loaded on one factor in the SEM but a number of items had comparatively low loadings or did not capture behavior but skills, learning experience or beliefs (see Appendix A). Seven items were excluded, leaving a parsimonious 5-item solution.

### **Self-disclosure measure**

Self-disclosure has been previously measured either through self-reports or behavioral observations through content-analysis (Joinson & Paine, 2007). Self-reported measures of self-

disclosure were used, for example, in a study on users' motivation to disclose personal information on online social networks (Krasnova et al., 2010). Participants were asked to what extent they believed that they had extensive, up-to-date profiles on social media and how often they shared updates. In another study, self-disclosure was measured through behavioral observations, as instances of neutral, positive, and negative personal information disclosure (Joinson, 2001). Trained coders reviewed transcripts of the interviews and noted occurrences of self-disclosure.

We adopted a behavioral observation approach to measure self-disclosure. However, we did not rely on a content analysis, but on a quantitative, survey-based approach. Based on the types of questions used in previous studies, we developed a questionnaire consisting of twelve questions about relationships, personality traits, demographics, personal finance, health, and education. Respondents were asked to disclose 12 pieces of personal information of varying sensitivity. Each piece of information was queried directly (for example, "How many close friends do you have?") and respondents could then choose to disclose this information in a text box or decline to disclose by ticking "I prefer not to answer this question." We then summed up the number of times each respondent provided information. Thus, the potential range of self-disclosure is from 0 (always selected "I prefer not to answer") to 12 (always disclosed). Appendix A provides the 12 self-disclosure questions. After the block on self-disclosure, we asked participants to rate the sensitivity of each self-disclosure question on a 0-100 slider. An index was created by averaging the information sensitivity across the 12 items.

#### **Privacy concerns, institution-based trust and personality trait measures**

We used three items from the widely applied "Global Information Privacy Concern" scale to measure privacy concerns (Malhotra, Kim, & Agarwal, 2004). The scale had a Cronbach's Alpha of 0.70, indicating sufficient internal consistence. The exact wording of all privacy concerns items can be found in Appendix A.

To control for trust, we used the institution-based trust construct from McKnight et al. (2002). This scale had a Cronbach's Alpha of 0.86. Again, Appendix A shows the wording.

Finally, we included the respondents' personality characteristics. To do so, we relied on the "very brief measure of the Big-Five personality domains" (Gosling, Rentfrow, & Swann, 2003). Each personality trait was measured with two items (see Appendix A for wording). Extraversion and emotional stability showed good reliability (Cronbach's Alpha of 0.80 and 0.78 respectively). The reliability for conscientiousness was slightly below the threshold of 0.7, with a Cronbach's Alpha of 0.69, and both openness to experience (Alpha = 0.46) and agreeableness (Alpha = 0.58) were considerably below the threshold. We decided to keep these constructs nevertheless due to their theoretical importance.

### **Method of analysis**

We used structural equation modeling (SEM) to test the research model, relying on robust maximum-likelihood estimation (MLR) in MPlus (Version 7). The MLR estimator was selected to account for possible non-normal distribution of error terms and heteroscedasticity (Byrne, 2012).

### **Results**

We first present descriptive results on the key dependent and independent variables. The participants frequently engage in self-quantification. The mean value across the self-quantification items is 3.87 and the median is 4.00 (out of 5.00).

Regarding the sensitivity of information, we found that respondents perceived the question "*How many sexual partners have you had?*" to be the most sensitive, with an arithmetic mean of 61 and a median of 73 (out of 100). The questions regarding financial information (savings and credit card debt) were also considered to be sensitive. The savings question received higher scores, with an arithmetic mean of 60 and a median of 68. The debt question had an arithmetic mean of 54 and a median of 60. The questions around participants'

favorite study subject, current height, and impatience were considered to be least sensitive with median values below 10. The mean value for sensitivity index for all questions was 35.04 (median=36). Although we had included several highly sensitive questions, on average the respondents did not perceive the questions to be very sensitive.

Privacy concerns were pronounced. The respondents reveal most concern about item 1, with an arithmetic mean of 4.20 (out of 5.00). However, items 2 (3.86) and 3 (3.58) also had high arithmetic mean values. Across all privacy concerns items, the arithmetic mean was 3.88 and the median 4.00, indicating high concern.

As the last column of Table B in Appendix B shows, respondents express moderate institution-based trust.

Figure 2 presents the results of the SEM. The model has sufficient model fit, with the goodness-of-fit indicators all being in the acceptable range: Chi-square=338.13; degrees of freedom=225; RMSEA=0.035; CFI=0.97; TLI=0.96; and SRMR=0.048. In another SEM, we included demographic information (age, gender, education) as control variables but none of them had a significant effect on self-quantification and self-disclosure. For the sake of parsimony, we therefore excluded the demographic variables from the final reported model.

#### FIGURE 2. "RESULTS OF THE SEM"

Of the hypotheses related to personality traits and self-quantification (H1-H5), H1, H2, and H5 are rejected. Neither extraversion, nor agreeableness, or openness to experience have a significant effect on self-quantification. By contrast, we found support for H3 and H4. Conscientiousness is the strongest driver of self-quantification and emotional stability has a negative effect. Thus, the more conscientious and the less emotionally stable individuals are, the more frequently they engage in self-tracking. The central hypothesis H6 was supported. Self-quantification has a small but positive and significant effect on self-disclosure in the context of the survey. Looking at the privacy-related hypotheses, H7 and H8 were rejected,

while H9 was supported. Privacy concerns do not lead to reduced self-disclosure and self-quantification but they result in lower levels of institution-based trust. Surprisingly, the effect of privacy concerns on self-quantification is positive, indicating that users with pronounced privacy concerns engage more heavily in self-quantification than users with fewer concerns. We will come back to this result in the discussion. Similarly, the evidence for institution-based trust is mixed, with H10 being rejected but H11 supported. Users who are more trusting do not disclose more data but they engage more frequently in self-quantification. Finally, H12 was supported, showing that perceived information sensitivity has a strong effect on self-disclosure.

## **Discussion and Conclusion**

### **Summary and Implications**

In this paper, we reported a quantitative survey study on self-quantification, self-disclosure, and privacy. We found that respondents showed general agreement with all the self-tracking items, as indicated by median values of 4 for all individual items used in the SEM. This concerns the whole process of self-quantification: collecting data, analyzing it, drawing conclusions, and learning from the data.

We discovered that self-quantification can be partly explained by personality variables, specifically conscientiousness and emotional stability. We discovered that trust and privacy concerns are positively associated with self-quantification. We also looked at self-disclosure by measuring users' self-disclosure directly with an index of 12 dichotomous items. Each item asked for a piece of personal information on a spectrum from not sensitive to very sensitive. Our assumption was that the more frequent self-quantifiers will be more likely to disclose personal information in our survey. This turned out to be the case. The sensitivity of the information and the extent of self-quantification were the only significant predictors for self-disclosure. By contrast, demographic characteristics, privacy concerns, and institution-based trust did not affect users' willingness to disclose personal information.

Our findings have implications for research into privacy, self-quantification, and self-disclosure. First, they show that self-quantification is a multi-faceted phenomenon that goes beyond simple data collection, with implications for self-disclosure beyond the context of personal informatics.

Second, self-quantification is associated with certain personality variables, namely emotional stability and conscientiousness. Agreeableness and extraversion are interpersonal character traits, while openness to experience, emotional stability, and conscientiousness are not (Costa, McCrae, & Dye, 1991; McCrae & Costa, 1989). This implies that self-quantification is associated with personality variables related to selfhood rather than to interpersonal interactions. Emotional stability and conscientiousness are composed of various personality traits and not all of them may be highly related to self-quantification. To make more accurate predictions about the behavioral implications of self-quantification, a comprehensive analysis of the phenomenon should be performed. A study of the effects of personality traits on self-quantification can serve as a good starting point.

Third, self-quantification is positively associated with institution-based trust and privacy concerns, while privacy concerns have a negative effect on trust. Because most self-tracking applications and wearables provide users with data through Internet-enabled algorithms, the positive effect of trust on self-quantification is understandable. In order to use self-tracking applications and wearables, users have to consent to online data collection and analysis. While the negative association between trust and privacy is consistent with the existing literature (Bart et al., 2005; Hoffmann et al., 2014), a positive effect of privacy concerns on self-quantification was surprising. The types of self-tracking applications the respondents use might partly explain this relationship. It is plausible that users with serious privacy concerns are more elaborate in choosing self-tracking applications and wearables. They may be more likely to invest their resources into more detailed screening of available self-

tracking options. Users with pronounced privacy concerns may screen more thoroughly for privacy-friendly tracking solutions by reading customer reviews or choosing premium versions of applications. Such screening efforts might result in using devices that offer more safety and better privacy policies.

Fourth, our findings suggest that self-quantification affects self-disclosure. However, this does not happen through the sensitivity of the information or reduced privacy concerns, meaning that another mechanism drives people's intention to disclose personal information in this context. There are several possible explanations. One explanation may be that when using self-tracking applications and devices occasionally, self-quantifiers experience a transformation of the concept of privacy. They may not feel sole ownership of their personal data and, instead, perceive it as a part of a larger information system.

Another way of tackling the mechanism through which self-quantification affects self-disclosure is by considering cognitive aspects of self-quantification. Sharing personal information with a self-tracking application or a wearable device regularly is an iterative process that may grow into a habit. This way, self-quantifiers learn to disclose their information upon request, given that the conditions of the request are similar to those when interacting with a self-tracking device or application. For example, if a user of a self-tracking application learns that providing an app with more personal data affects the accuracy of the algorithm, this learned logic may spill over to other situations.

Finally, qualitative research assumes that the main reason why people engage in self-quantification is performance optimization in order to get more control over their lives. Our findings suggest that self-quantifiers are more prone to disclose their personal information beyond the personal use of data. By disclosing more information, people may expose themselves to risks, varying from extensive targeting by advertising agencies to fraud. As a



result, an important question can be raised: Do self-quantifiers indeed gain control of their lives or is it possible that by disclosing more information they lose control?

### **Limitations and Future Research**

Our study is subject to a number of limitations that point to possible future research in this area. First, our sample is relatively small and covers a broad range of self-quantification applications and scenarios. Future research might want to look more specifically into certain domains such as mood tracking, relationship tracking, and diet tracking. On the other hand, it might also use broader and more representative samples, for example by collaborating with the application designers. In that regard, a second limitation concerns the lack of behavioral data, except for the dependent variable of self-disclosure. We encourage future research on self-quantification to combine different data sources and enrich quantitative self-reports with qualitative and contextual data as well as behavioral data. Third, given the newness of the topic, our study is largely exploratory and lacks a sophisticated theoretical framework. Future research should apply existing social science theories or develop new ones to describe self-quantification and relate it to existing social developments. Fourth and finally, we covered one point in time and our study is thus cross-sectional. Future research should apply longitudinal designs to observe and explain changes over time and to better account for causality.

Despite these limitations, we hope to contribute to a better understanding of the important trend of self-quantification with our research. While more research has to be done, this paper can be a starting point for the quantitative study of the phenomenon.

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Figures

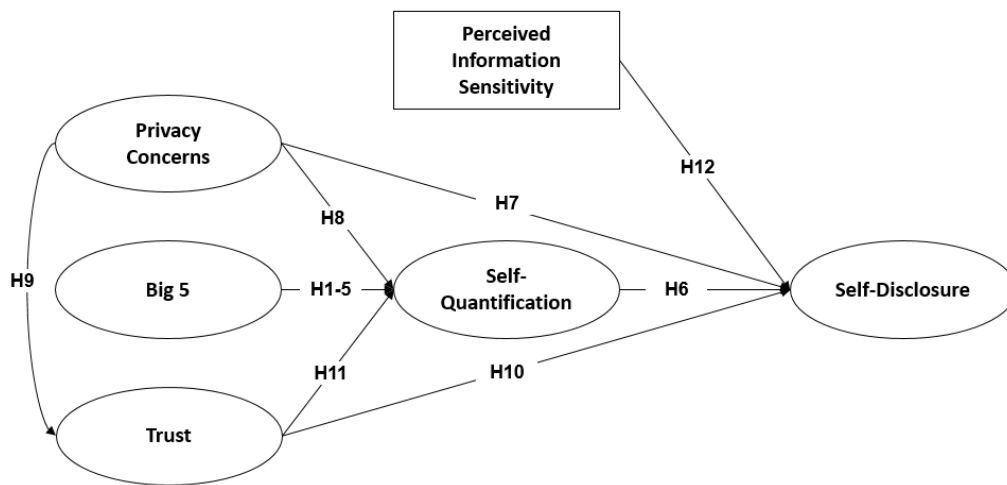
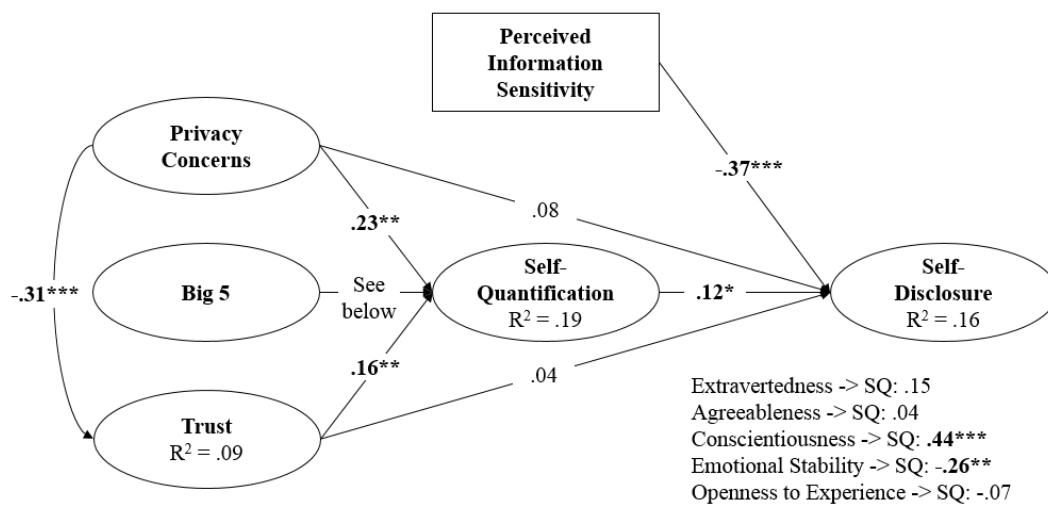


Figure 1. Research Model



\*\*\*  $p < 0.001$ ; \*\*  $p < 0.01$ ; \*  $p < 0.05$

Figure 2. Results of the SEM



## Appendix

### Appendix A: Questionnaire

<p><b>Self-Quantification</b></p> <p>(based on stage-based model of personal informatics systems by Li Dey, &amp; Forlizzi, 2010)</p>	<p>Please indicate to what extent you agree with the following statements. Please refer to your use of both devices (e.g. Apple Watch) and applications (e.g. MyFitnessPal).</p> <hr/> <p><i>I regularly collect data on my behavior using self-tracking devices.</i></p> <hr/> <p><i>It is important for me to collect data on my behavior</i></p> <hr/> <p><i>I monitor my collected data regularly.</i></p> <hr/> <p><i>I analyze my data regularly.</i></p> <hr/> <p><i>I compare my personal data from different periods in time.*</i></p> <hr/> <p><i>I can recognize patterns in the data that I have collected using self-tracking devices.*</i></p> <hr/> <p><i>I make connections between my behavior and the data that I get from self-tracking devices.</i></p> <hr/> <p><i>I constantly get new insights about how my body and mind works from the data collected with self-tracking devices.*</i></p> <hr/> <p><i>Data collected with self-tracking devices helps me to make better decisions in my everyday life.*</i></p> <hr/> <p><i>I have learned a lot about myself from the data collected with self-tracking devices.*</i></p> <hr/> <p><i>I believe that collecting and analyzing data from self-tracking devices helps me to improve my well-being.*</i></p> <hr/> <p><i>I constantly adjust my behavior based on the data/feedback I receive from self-tracking devices.*</i></p>
<p><b>Privacy Concerns</b></p> <p>(based on Malhotra et al., 2004)</p>	<p><i>All things considered, the Internet could cause serious privacy problems.</i></p> <hr/> <p><i>Compared with other subjects on my mind, personal privacy is very important.</i></p> <hr/> <p><i>I am concerned about threats to my personal privacy today.</i></p>
<p><b>Self-Disclosure</b></p> <p>(self-developed, aggregate self-disclosure as the</p>	<p><i>How many close friends do you have?</i></p> <hr/> <p><i>To what extent do you consider yourself to be impatient with other people?</i></p> <hr/> <p><i>What was/is your favorite subject of study during your education?</i></p>

number of questions respondents decided to answer/did not decline to answer)	<i>Do you identify with any religion or religious group? If so, please specify.</i>
	<i>What is your current job title? If unemployed, in education or retired, please specify so.</i>
	<i>How much money do you have saved up?</i>
	<i>How much credit card debt do you have?</i>
	<i>Do you have any medical conditions? If so, specify below.</i>
	<i>What is your current body weight?</i>
	<i>What is your current height?</i>
	<i>How many sexual partners have you had</i>
	<i>Have you every cheated on your partner by having sexual intercourse with someone outside a committed relationship?</i>
<b>Institution-based trust</b>  (McKnight et al., 2002, structural assurance of the web)	<i>The Internet has enough safeguards to make me feel comfortable using it to transact personal business.</i>
	<i>I feel assured that legal and technological structures adequately protect me from problems on the Internet.</i>
	<i>I feel confident that encryption and other technological advances on the Internet make it safe for me to do business there.</i>
	<i>In general, the Internet is now a robust and safe environment in which to transact business.</i>
<b>Big-Five Personality Characteristics</b>  (Gosling et al., 2003)	In the box below you will find a number of personality traits that may or may not apply to you. Please, read the traits carefully and specify to what extent do you agree with the statements. You should consider the extent to which the pair of traits applies to you, even if one characteristic applies more strongly than the other.
	<i>I am extraverted and enthusiastic. (EXT)</i>
	<i>I am critical and quarrelsome. (AGR – reverse)</i>
	<i>I am dependable and self-disciplined. (CON)</i>
	<i>I am anxious and easily upset. (EMO – reverse)</i>
	<i>I am open to new experiences and complex. (OPE)</i>
	<i>I am reserved and quiet. (EXT – reverse)</i>
	<i>I am sympathetic and warm. (AGR)</i>
	<i>I am disorganized and careless. (CON – reverse)</i>
	<i>I am calm and emotionally stable. (EMO)</i>

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*I am conventional and uncreative. (OPE – reverse)*

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\*=not included in SEM because of low loadings or not measuring behavior but skills

Table A. Questionnaire of the survey

### Appendix B: Measurement Model

Construct	Item	Std. loading	t-values	R <sup>2</sup>	$\alpha$	C.R.	AVE	Descriptive statistics
<b>Self-Quantification (SQU)</b>	squ1	0.877	44.192***	0.769	0.92	0.92	0.69	Mean: 3.87 Median: 4.00 Std. deviation: 1.00
	squ2	0.777	28.050***	0.604				
	squ3	0.866	42.454***	0.750				
	squ4	0.861	41.008***	0.741				
	squ5	0.785	29.773***	0.617				
<b>Privacy Concerns (PRI)</b>	pri1	0.600	12.611***	0.361	0.70	0.72	0.46	Mean: 3.88 (1-5) Median: 4.00 Std. deviation: 0.99
	pri2	0.678	14.221***	0.460				
	pri3	0.728	14.987***	0.530				
<b>Institution-Based Trust (TRU)</b>	tru1	0.815	29.790***	0.664	0.86	0.86	0.61	Mean: 3.22 (1-5) Median: 3.75 Std. deviation: 1.04
	tru2	0.739	23.361***	0.546				
	tru3	0.780	25.699***	0.609				
	tru4	0.771	25.992***	0.594				
<b>Extraversion (EXT)</b>	ext1	0.957	10.274***	0.916	0.80	0.83	0.71	Mean: 3.69 (1-7) Median: 3.50 Std. deviation: 1.82
	ext2	0.707	9.002***	0.500				
<b>Agreeableness (AGR)</b>	agr1	0.763	8.257***	0.582	0.58	0.62	0.46	Mean: 5.28 (1-7) Median: 6.00 Std. deviation: 1.54
	agr2	0.570	8.415***	0.325				
<b>Conscientiousness (CON)</b>	con1	0.799	17.873***	0.638	0.69	0.71	0.56	Mean: 5.54 (1-7) Median: 6.00 Std. deviation: 1.32
	con2	0.682	14.658***	0.465				
<b>Emotional Stability (EMO)</b>	emo1	0.740	13.640***	0.547	0.78	0.80	0.67	Mean: 5.08 (1-7) Median: 5.50 Std. deviation: 1.56
	emo2	0.894	18.553***	0.799				
<b>Openness (OPE)</b>	ope1	0.716	7.639***	0.513	0.46	0.51	0.36	Mean: 5.09 (1-7) Median: 5.00 Std. deviation: 1.47
	ope2	0.438	5.451***	0.192				
<b>Criterion</b>		$\geq 0.5$	min*	$\geq 0.4$	$\geq 0.7$	$\geq 0.6$	$\geq 0.4$	

$\alpha$  = Cronbach's Alpha; C.R. = composite reliability; AVE = average variance extracted. Average, median and standard deviation calculated per item and then averaged across items for each construct; N=374.

Table B. Measurement model

	<b>AVE</b>	<b>SQU</b>	<b>PRI</b>	<b>TRU</b>	<b>EXT</b>	<b>AGR</b>	<b>CON</b>	<b>EMO</b>
<b><i>SQU</i></b>	0.69							
<b><i>PRI</i></b>	0.46	0.06						
<b><i>TRU</i></b>	0.61	0.01	0.10					
<b><i>EXT</i></b>	0.71	0.01	0.00	0.00				
<b><i>AGR</i></b>	0.46	0.04	0.02	0.01	0.06			
<b><i>CON</i></b>	0.56	0.11	0.05	0.00	0.03	0.36		
<b><i>EMO</i></b>	0.67	0.03	0.04	0.01	0.10	0.31	0.47	
<b><i>OPE</i></b>	0.36	0.03	0.06	0.00	0.21	0.22	0.24	0.30

Squared correlations between the constructs are shown; AVE = average variance extracted

*Table C. Discriminant validity test (Fornell Larcker criterion)*