The Curse of Quantified-Self: An Endless Quest for Answers

Niels van Berkel
University of Oulu, Finland
niels.van.berkel@ee.oulu.fi

Chu Luo
University of Oulu, Finland
chu.luo@ee.oulu.fi

Denzil Ferreira
University of Oulu, Finland
denzil.ferreira@ee.oulu.fi

Jorge Goncalves
University of Oulu, Finland
jorge.goncalves@.ee.oulu.fi

Vassilis Kostakos
University of Oulu, Finland
vassilis@ee.oulu.fi

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than the author(s) must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from Permissions@acm.org.

UbiComp/ISWC '15 Adjunct, September 7–11, 2015, Osaka, Japan.
ACM 978-1-4503-3575-1.
http://dx.doi.org/10.1145/2800835.2800946

Abstract
Quantified Selfers are individuals that take a proactive stance to collect and act upon their personal data. However, these endeavours towards a better insight into one's life often do not last long. An important challenge for QS is sustaining data collection over a long period of time (*i.e.*, months, years, decades). In this paper we discuss the drivers, needs and concerns of longitudinal QS-data collection. We argue that to support longitudinal QS various obstacles have to be overcome, including i) integration and sharing of data between a variety of (new) devices, ii) incorporating human input for psychological data collection and iii) providing answers to the questions people really have.

Author Keywords
Quantified-self; personal informatics; wearables; sensing; context; ubiquitous computing;

ACM Classification Keywords
H.5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous;

Introduction
A Quantified-Selfer (QS'er) is an individual engaged in self-tracking of biological, physical, behavioural, or environmental information [2]. These individuals take a proactive stance to collect and potentially act upon

their data. Collection and tracking of this data is increasingly achieved using a combination of hardware and software. The number of devices capable of capturing QS-data has increased drastically in recent years: smartphones, smartwatches, fitness trackers and wearable devices all contain a multitude of sensors and applications [2].

An important challenge for QS is sustaining data collection over a long period of time (*i.e.*, months, years, decades). This challenge stems from the fact that the devices used to capture QS-data often become obsolete or abandoned by their owners within a couple of months [12]. A recent survey of 6,223 US adults revealed that 50% of respondents no longer use their activity tracker and a third of those stopped using it within six months [12]. Manufacturers update their devices frequently in an attempt to convince their intended user base to upgrade their current device. This rapid change makes it more challenging to collect QS-data longitudinally: competing manufacturers lack a standard in QS-data storage, often requiring one to start with a blank slate.

In this paper we discuss the drivers, needs and concerns of longitudinal QS-data collection. We argue that to support longitudinal Quantified-Self, QS developers need to consider both human (*i.e.*, individual and collective) and technological factors for longitudinal QS-data collection.

Related Work

Tracking one's data is not a new idea, *e.g.*, athletes commonly make detailed notes on nutrition, training sessions, and sleep [5]. However, the plethora of devices today make it feasible to collect and analyse heterogeneous kinds of personal data on a larger scale and with increased granularity [14]. We identified publications dedicated to QS mainly from three major conferences (*i.e.*, MobileHCI, CHI and UbiComp) since 2010 and summarized our findings in **Table 1**.

Insights provided	Ref.	Year	N	Length	Data collection	Reward	Visibility
Classroom activities	[9]	2010	9	3w	Hand-held device	Y	Semi-shared
Driving style	[4]	2011	37	3 trips	Car driving metrics	N	Individual
Conversation skills	[1]	2011	35	3w	Social media	Y	Individual
UV radiation	[6]	2011	2	1d	Wearable sensors	N	Individual
Sleep quality	[10]	2012	4	2w	Sensor suite	Y	Individual
Firefighter performance	[7]	2013	71	148h	Smartphone sensors	N	Shared
Gamified physical activity	[20]	2014	40,59	2w; 10d	Smartphone sensors	N; Y	Leaderboard
Gym exercise performance	[16]	2014	7	20x 10 exercises	Exercise mat	N	Individual
Habit formation	[15]	2015	133	4w	SMS self-report	Y	Individual
Personality traits	[19]	2015	124	-	Social media	Y	Individual

Table 1: QS-related studies reviewed from HCI conferences (2010–2015).

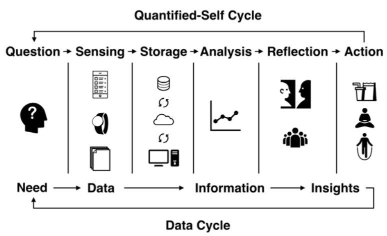

Figure 1 - Different stages of QS and how a user's need for data leads to insights through its collection and conversion from data into information.

The majority of studies with QS applications have a relative short duration and few participants. We believe this is due to several key challenges present at different stages in the QS and data cycle (see **Figure 1**). To encourage participation, 5/11 of the reviewed studies compensated the participants for their time and data. Moreover, a minority of studies (3/11) used data-sharing to establish social comparison within a group of users, including one instance based on gamification. While these studies provide incremental steps to fully understand QS practices, we do believe that both qualitative and quantitative (large scale) longitudinal user studies are necessary to further understand QS users' *habit formation*, the effect of *social motivation*, *goal reinforcement*, and matching users' *lifestyle* [12].

Challenges of Quantified-Self & Data Cycles

QS can be considered as a cycle [13] (**Figure 1**): a ***need*** is investigated (**Question**) through the collection of ***data***, *e.g.*, smartphone (**Sensing**). Data is then stored in a certain format, *e.g.*, on a computer or in the cloud (**Storage**). Data becomes ***information*** through data **Analysis** (*i.e.*, statistical or visualization tool). QS'ers then can **Reflect** on the information alone or with others. A QS'er may gain ***insight*** and **Act** accordingly (*e.g.*, diet, exercise). Note that the cycle may start over at the analysis or reflection stage, if the information is poor or not insightful, and may repeat itself several times for more data. In the following sections the stages succeeding the question stage are introduced alongside their respective challenge(s) to longitudinal QS (summarized in **Table 2**).

Sensing

To reduce the burden of data logging on the user, sensing should *be as autonomous as possible*. Device-based data collection is increasingly popular (**Table 1**) and convenient, data is collected and often synched automatically. Since users own devices of diverse form factors, data collection and integration remain problematic. The *ownership* of these devices may also change, and one device may be actively used by a variety of (unrelated) people. Hence, future QS applications have to support data sensing from a variety of platforms and hardware.

Lastly, current hardware sensing methods are unable to capture psychological aspects of human life. Human-based sensing methods are necessary for collecting real-time and *in-situ* data on these aspects of human life, *e.g.*, emotions, stress [18] and mood [8]. Such methods include the Experience Sampling Method (ESM) [11] and the Ecological Momentary Assessment (EMA) [18]. Both methods reduce reliance on the participants' memory, as opposed to retrospective interviews and diary logs.

Storage

Data has to be *accessible* to offer value during the subsequent stages of QS. As data sensing takes place on diverse platforms, QS requires a centralized data repository. The most suitable location is debatably the "cloud": elastic computing allows users to increase storage space as needed and offers data safeguards.

However, it still remains unclear *how* one should store this data. The recent advent of "big-data" database structures has introduced *NoSQL* (Not only SQL). NoSQL offers the ability to jointly store data objects that are structurally different but pertain to the same context. For QS sensing this means jointly storing data from two different devices for the same physical

QS Stage	Challenge(s)
Sensing	Data integration Human sensing
Storage	Accessible to both other software and devices
Analysis	Increasing # of data sources
Reflection	Provide holistic view of data
Action	Provide necessary insights

Table 2: Summarized challenges for longitudinal QS per stage following the construction of a question.

activity. This allows users to collect the same "kind" of information, regardless of their device. On the downside, much privacy related information could be obtained through one data breach.

Analysis

Wearable owners expect instant "gratification" from their devices' data, *e.g.*, "*How am I doing today? Did I take enough steps? How many calories have I burnt?*". It is therefore imperative that such devices provide users with instant data analytics and metrics (*i.e.*, *information*). Converting data into information increases in complexity with the number of data sources. The integration of data introduces technical challenges, but can provide richer information when compared to sensing from only a single modality [10].

To the best of the authors' knowledge, no integrated and *scalable* QS analysis tool exists today. Previous work focused on visualizing [4,6] or building a custom application to collect QS-data [16]. Although necessary, we must emphasize on building QS-tools that provide a wider and evolving perspective on one's self-data, thus supporting the QS and data cycle (**Figure 1**). To realize such a tool, sensor values and human input data will have to be integrated for a broader view of one's life.

Reflection

Most QS applications fail to answer users' questions [14], thus hindering self-reflection. Li et al. note that users have significant trouble identifying the factors that influence their state over a long term, especially when multiple devices or applications are involved [14]. A key challenge for long-term QS will thus be to bring the data collected from a variety of devices together into a uniform overview, without relying on complex visualizations graspable by only a small subset of the population. Alternatively, a group of QS'ers sharing data amongst themselves (*i.e.*, Quantified Communities) are transforming the understanding of significant areas such as personalized health care [17]. Future QS-tools should take advantage of crowd-sensing to aid on breaking down the big picture into smaller units of information: a reflection of each individual's data in combination with others' data.

Action

After reflection, the user may undertake a certain action. The action step is dependent on reflection and insight. In other words, the *data must provide insight for the action step to take place*, *e.g.*, encourage the user to minimize the amount of time exposed to a high level of UV and to use sunscreen more often [6].

Discussion

The Never-Ending Quest for Answers

A QS'er is primarily motivated to collect data to answer a question about one-self. Once the answer is obtained (either by one-self or within a community effort), a QS'er can either transition to a different question or (temporarily) stop self-tracking activities. Alternatively, if the effort is inconclusive then new data may be required. Thus, depending on any remaining or newly defined questions, the QS cycle may start over again. So, we should not expect a participant to collect the *same* QS-data for a long time.

This becomes pertinent in studies where an overwhelming amount of perfunctory results has been collected, due to inactive participation [3,15]. Whereas in HCI studies participants have traditionally received rewards for their time and data, in QS studies rewards alone may not be sufficient. Hence, we argue that inactive participation can be considered as a consequence of self-accomplishment.

Transient Self

A drawback of QS applications is their *immutable* design [3,12]: they are built to collect a pre-determined set of data and provide a visualization and/or report after analysis. Hence, to engage longitudinal QS-data collection, a QS-tool needs to adapt to the users' dynamics of questions. A successful example is health care, where new apps and tools are built for patients to track different disease symptoms over time [17] as they become afflicted. This means that QS applications should allow integration of new data from diverse sources, and enable users to introduce new questions into their current QS quest.

Additionally, users can act as sensors for various metrics that QS applications cannot measure using hardware/software directly. Using for example ESM/EMA, the user can provide valuable and *mutable* data that is (seemingly) impossible to collect using traditional sensors.

Conclusion

A challenge for QS is the longitudinal adoption of tools and services. Here we present a 6-stage model of Quantified Self, and the challenges for each stage pertaining to this *longitudinal* aspect of QS. These challenges (**Table 2**), can be summarized to three key elements. First; an increase in devices used by QS'ers will require extensive data sharing capabilities between these devices. Secondly, in order to achieve a more complete understanding of a person's self, the analysis should include psychological data. This data can be obtained through human input. Lastly, in order to be of value to people's lives, QS applications should provide answers that people are really looking for. Our analysis identifies future research for the community.

Acknowledgements

This work is partially funded by the Academy of Finland (Grants 276786, 285062, 286386), and the European Commission (Grants PCIG11-GA-2012-322138 and 645706-GRAGE).

References

1. Jilin Chen, Rowan Nairn and Ed Chi. 2011. Speak Little and Well: Recommending Conversations in Online Social Streams. In *Proc. CHI*, 217-226. http://dx.doi.org/10.1145/1978942.1978974.
2. Eun K. Choe, Nicole B. Lee, Bongshin Lee, Wanda Pratt and Julie A. Kientz. 2014. Understanding Quantified-selfers' Practices in Collecting and Exploring Personal Data. In *Proc. CHI*, 1143-1152. http://dx.doi.org/10.1145/2556288.2557372.
3. Andrea Cuttone and Jakob E. Larsen. 2014. The Long Tail Issue in Large Scale Deployment of Personal Informatics. In *Proc. UbiComp: Adjunct Publication,* 691-694. http://dx.doi.org/10.1145/2638728.2641319.
4. Ronald Ecker, Philipp Holzer, Verena Broy and Andreas Butz. 2011. EcoChallenge: A Race for Efficiency. In *Proc. MobileHCI*, 91-94. http://dx.doi.org/10.1145/2037373.2037389.
5. The Economist. Counting every moment. 2012. Retrieved May 25, 2015 from http://www.economist.com/node/21548493
6. Thomas Fahrni, Michael Kuhn, Philipp Sommer, Roger Wattenhofer and Samuel Welten. 2011. Sundroid: Solar Radiation Awareness with Smartphones. In *Proc. UbiComp*, 365-374. http://dx.doi.org/10.1145/2030112.2030162.

7. Sebastian Feese, Bert Arnrich, Gerhard Troster, Michael Burtscher, Bertolt Meyer and Klaus Jonas. 2013. CoenoFire: Monitoring Performance Indicators of Firefighters in Real-world Missions Using Smartphones. In *Proc. UbiComp*, 83-92. http://dx.doi.org/10.1145/2493432.2493450.
8. Javier Hernandez, Mohammed Hoque, Will Drevo and Rosalind W. Picard. 2012. Mood Meter: Counting Smiles in the Wild. In *Proc. UbiComp*, 301-310. http://dx.doi.org/10.1145/2370216.2370264.
9. Sen H. Hirano, Michael T. Yeganyan, Gabriela Marcu, David H. Nguyen, Lou A. Boyd and Gillian R. Hayes. 2010. vSked: Evaluation of a System to Support Classroom Activities for Children with Autism. In *Proc. CHI*, 1633-1642. http://dx.doi.org/10.1145/1753326.1753569.
10. Matthew Kay, Eun K. Choe, Jesse Shepherd, Benjamin Greenstein, Nathaniel Watson, Sunny Consolvo and Julie A. Kientz. 2012. Lullaby: A Capture & Access System for Understanding the Sleep Environment. In *Proc. UbiComp*, 226-234. http://dx.doi.org/10.1145/2370216.2370253.
11. Reed Larson and Mihaly Csikszentmihalyi. 2014. The Experience Sampling Method. In *Flow and the Foundations of Positive Psychology,* Springer Netherlands, 21-34. http://dx.doi.org/10.1007/978-94-017-9088-8_2.
12. Dan Ledger and Daniel McCaffrey. 2014. Inside Wearables, How the Science of Human Behavior Change Offers the Secret to Long-Term Engagement. Endeavour Partners.
13. Ian Li, Anind K. Dey and Jodi Forlizzi. 2010. A Stage-based Model of Personal Informatics Systems. In *Proc. CHI*, 557-566. http://dx.doi.org/10.1145/1753326.1753409.
14. Ian Li, Anind K. Dey and Jodi Forlizzi. 2011. Understanding My Data, Myself: Supporting Self-reflection with Ubicomp Technologies. In *Proc. UbiComp*, 405-414. http://dx.doi.org/10.1145/2030112.2030166.
15. Katarzyna Stawarz, Anna L. Cox and Ann Blandford. 2015. Beyond Self-Tracking and Reminders: Designing Smartphone Apps That Support Habit Formation. In *Proc. CHI*, 2653-2662. http://dx.doi.org/10.1145/2702123.2702230.
16. Mathias Sundholm, Jingyuan Cheng, Bo Zhou, Akash Sethi and Paul Lukowicz. 2014. Smart-mat: Recognizing and Counting Gym Exercises with Low-cost Resistive Pressure Sensing Matrix. In *Proc. UbiComp*, 373-382. http://dx.doi.org/10.1145/2632048.2636088.
17. Melanie Swan. 2009. Emerging Patient-Driven Health Care Models: An Examination of Health Social Networks, Consumer Personalized Medicine and Quantified Self-Tracking. Int. J. Environ. Res. Publ. Health 6, 2, 492-525. http://dx.doi.org/10.3390/ijerph6020492.
18. Rui Wang, Fanglin Chen, Zhenyu Chen, Tianxing Li, et al. 2014. StudentLife: Assessing Mental Health, Academic Performance and Behavioral Trends of College Students Using Smartphones. In *Proc. UbiComp*, 3-14. http://dx.doi.org/10.1145/2632048.2632054.
19. Yang Wang, Liang Gou, Anbang Xu, Michelle X. Zhou, Huahai Yang and Hernan Badenes. 2015. VeilMe: An Interactive Visualization Tool for Privacy Configuration of Using Personality Traits. In *Proc. CHI*, 817-826. http://dx.doi.org/10.1145/2702123.2702293.
20. Oren Zuckerman and Ayelet Gal-Oz. 2014. Deconstructing gamification: evaluating the effectiveness of continuous measurement, virtual rewards, and social comparison for promoting physical activity. Personal and Ubiquitous Computing 18, 7, 1705-1719. http://dx.doi.org/10.1007/s00779-014-0783-2.