Beyond Quantified Self

Data for Wellbeing

Toronto, Canada

April 27th, 2014

Organizers:
Jochen Meyer
Steven Simske
Katie Siek
Cathal Gurrin
Hermie Hermens

CHI 2014
One of a CHInd
Toronto, Canada
Table of Contents

• Design Considerations for Socially Sharing Quantified Self Data 1
  Daniel A. Epstein, Elizabeth Bales and Sean A. Munson

• How People Use Smartphone Apps to Manage Long Term Conditions 5
  Kit Huckvale and Cecily Morrison

• Whats Next for Quantified Health: In-Context Decision Support for People with Chronic Conditions 10
  Nikki Pfarr, Dave McColgin and Matthew Jordan

• Empowering people to test their own quantifiable hypotheses with pervasive displays 14
  Farahnaz Yekeh, Judy Kay, Robert Kummerfeld and Margaret Allman-Farinelli

• I Am Not the Patient: Design Challenges in Self-Screening Medical Device 18
  Chen Zhao, Dawn Koh, Ricardo Sosa and Ngai-Man Cheung

• Community Level Health Data: Looking at Real-Time Dating Sites 22
  Mark Handel and Irina Shklovski

• Logging Phone Usage to Understand Health and Wellbeing 26
  Alistair Morrison, John Rooksby and Mattias Rost

• There is More to Well-being than Health Data Holistic Lifelogging through Memory Capture 30
  Tilman Dingler, Alireza Sahami and Niels Henze

• Towards Mental Balance: A Quantified Self Approach for Communicating Mental State 34
  Robert Beaton and Scott McCrickard

• Inbodied5 and Future Ghosts: sense-making for QS Wellbeing Support 38
  M. C. Schraefel
Abstract

Introduction
Being healthy is one of the fundamental wishes of the human being. Research has discussed the potential of eHealth systems for a long time. eHealth interventions aim to help sick or vulnerable people e.g. to deal with chronic diseases more independently, to mitigate an unhealthy behavior, or to improve the doctor-patient communication. However, helping the healthy person to stay healthy (what we will subsequently call wellbeing) takes a different perspective that requires careful consideration: Aspects such as lifelong use or data ownership must be seen in a different light, and our research approaches e.g., on evaluation may need to be adopted.

Monitoring the user’s current behavior and health is one of the fundamental measures to be taken. While research is frequently addressing monitoring in the context of e.g., behavior change, aspects such as long term usability in real life hinder the direct adoption of the research results to wellbeing. E.g., for activity monitoring, high-precision accelerometers may be used for fairly precise measurements of a person’s behavior, but the devices are not suitable for daily use in a broader group, so the steps per day are still a dominating measure for a person’s level of activity. The Quantified Self movement has attracted attention to personal health monitoring and is some kind of pioneer demonstrating possibilities and stimulating new ideas. However the average user is usually not interested in technology and data, but rather in easily understandable information and knowledge about one’s own health.

Challenges
There is an inherent trade-off between quality of data – in terms of precision, reliability and availability – on the one hand, and usability and user’s effort for data acquisition on the other. More precise and more reliable data usually has an impact on usability and user’s effort. Hardware improvements by better and cheaper sensors alone cannot solve this problem. E.g. sensors for heart rate, heart rate variability or skin conductance need skin contact, thus must be worn directly on the body. This may be considered unacceptable, too uncomfortable, or it may interfere with daily life, e.g., hygienic requirements for nurses or cooks.

The perceived effort of monitoring is furthermore influenced by the user’s personal motivation. Changes in life such as the start of the career or the birth of a child changes the way people think about their own health and raise interest in, e.g., weight control or cardiovascular prevention, which in turn increases the willingness to use specific health systems at the cost of higher efforts. On the other hand people may not want to monitor in phases of stable health state or as other aspects of life gain more importance.

Creating systems to empower people to effectively manage their personal health requires an interdisciplinary approach for data collection, aggregation and reflection. Collecting data involves e.g., designers, HCI experts, sensor developers, and device producers. Data aggregation requires e.g., data analytics and big data, visualization, psychology, social behavior, and machine learning, to make sense of the data and make recommendations. And reflection again brings in design, HCI, hardware and devices. Collection, aggregation, and reflection mutually influence each other: We can only aggregate what we can measure, we should only aggregate what the user will reflect upon, and we can only offer reflection about measurable values. Therefore the involved disciplines need to work together before we can build effective systems for health behavior maintenance and change.

One of the key aspects is the required quality of data. Medical experts ask for data that is as precise and complete as possible. Data analysts point out that data is imprecise and unreliable. Designers appraise ease of use higher than precision of data. And the user comes with changing interests and motivation over time, resulting in changing needs in his current and also past data.
Design Considerations for Socially Sharing Quantified Self Data

Abstract
Social sharing has been widely integrated into self-tracking tools. By aggregating design recommendations from the prior work on these tools, we can offer general design principles for sharing personally collected data. In this work, we break down sharing into a series of dimensions and offer design considerations for each. From these considerations, we can prescribe how applications in new, unexplored areas can effectively integrate social sharing.

Author Keywords
Personal informatics; social sharing

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

Introduction
Devices and applications for collecting and monitoring personal data have become ubiquitous. From their inception, many of these tools have included features for sharing with others. Even when sharing has not been technically supported, users of these systems have found other ways to share their data [1]. The data collector can benefit by sharing their data, getting encouragement, support, recommendations, and feedback from experts or friends [6]. Tool developers are also heavily incentivized to make social sharing as
easy as possible, as any posts about their tools to 
social networks serve as free advertisements. 

With the potential benefits of social sharing, it is 
unsurprising that there has been extensive prior work 
in this area. However, most studies consider a single 
point in the design space, either examining how a 
preexisting community shares or developing a novel 
way to share. As two examples, Teodoro & Naaman 
explore how Twitter has been used to share physical 
activity information with a wide-reaching, multi-
urpose social network site [7], while Curmi et al. 
developed a new tool to share heart rate data in real 
time [2]. Each publication in this space provides design 
knowledge specific to the domain or sharing modality, 
while offering suggestions for how to extend to other 
related systems. By examining the prior work, we can 
start to offer more general design recommendations for 
sharing personally collected data.

In this workshop paper, we present the beginnings of a 
formalization and review of this 
design space. We 
analyze the literature on sharing to develop a series of 
dimensions that describe what has been tried, what has 
been successful, and what areas need more attention. 
While the constraints of a workshop paper do not allow 
us to fully elaborate on all of dimensions and requires 
us to focus on a few examples of the prior work, it 
provides a short explanation of what we are exploring. 
We hope that this workshop will serve as a forum to 
discuss design choices and provide additional points in 
the literature space with which we are less familiar.

Type of Data Collected 
Quantified Selfers track in a wide variety of domains, 
often going so far as to create their own tools for 
recording and reviewing data [1,5]. Sharing of 
manually collected records occurs in meetups in the 
Quantified Self community [1] or one-off posts to social 
networks [7]. While automatic tools are less flexible, 
they potentially create more reliable records and 
require less overhead. These tools often make the 
process of sharing simple, as seen by the “tweet” and 
“like” buttons prominent in figure 1.

The domain of data collected is also relevant to sharing. 
Location sharing has been researched extensively [4], 
and is integrated into the Google+ and Path social 
network sites. Sharing of biometric data such as heart 
rate is an emerging field [2], but has not reached 
mainstream adoption.

Design Considerations 
When discussing whether a domain is appropriate to 
share, an important question to ask is "Will the 
recipient find the information interesting or useful?" 
While this question is subjective, a survey could provide 
insights into the interest level of recipients.

Another question to ask when considering a domain is 
whether the data is too private to consider sharing. 
Much work in location sharing [4] and physical activity 
[3] has asked this question. Munson et al. present a 
literature review surrounding privacy concerns when 
sharing personal data [6].

Preprocessing of Information Shared 
Current tracking applications can record data 
constantly, gathering heart rate, location, or physical 
activity on a minute-by-minute basis [2,3]. Prior to 
sharing, this data can be aggregated in any number of 
ways. Figure 2 shows two such options from data 
collected by the commercial application Moves:

Figure 1. Sharing a badge gained 
with a FitBit, a commercial 
pedometer.

Figure 2. A fine-grained lifelog 
and corresponding summary 
collected from the commercial 
application Moves.
detailed lifelog showing exact locations and durations can be shared directly, or only the total distance traveled and mode. Other applications enable detailed sharing of a specific activity, such as the Strava application reporting a bicycling route.

Some systems designers have considered editing data prior to sharing (or choosing to share less granular information, such as at the grocery store instead of a specific location) to prevent disclosure of potentially private information [3,4]. In these systems, privacy is in tension with honesty when sharing, as the use of these features may be viewed as lying to recipients.

**Design Considerations**
With a continuum of sharing granularities, there is a tension between providing enough details to meet the goal of sharing and oversharining. With just a high-level summary, finding opportunities for shared events such as carpooling or going for a walk when both parties are available become difficult, but providing a more detailed log may overwhelm the recipient [3].

**Temporality of Sharing**
Social network sites use a broadcast model for posting, where an action, either automatic by an application or initiated by the user, triggers making a post. Both automatic and manually triggered posts exist in applications, such as the accidental post in figure 3.

Another approach is to constantly stream data to a dedicated page, and let recipients give feedback at their discretion. While HeartLink uses this approach for sharing fine-grained data about a specific event [2], this is akin to providing information in a personal profile. Figure 4 is one such profile, combining standard information about the user with their latest data.

**Design Considerations**
Temporality of sharing is relatively underexplored. We hypothesize that automatically shared posts, such as figure 3, are less likely to generate feedback from recipients than self-curated posts.

**Recipients of Information**
The target audience of a post can vary widely. Sharing to general social network sites provides social accountability and enable sharers to reach a large audience [7]. This contrasts with sharing on a social network site dedicated to a specific device or type of data tracked. These recipients have a baseline understanding of and interest in the data being shared.

People also express interest in sharing with a smaller group consisting of close friends or family members [3,4]. This may be preferable if the data is beneficial to share, but personally sensitive.

**Design Considerations**
Different recipients offer different potential benefits. By sharing with a general social network site, more people are likely to see a post, but they may be more inclined to ignore it or may not receive value from reading it. Close friends or family members often provide opinions that matter more to the recipient, but the breadth of expertise is more limited. Using a dedicated social network site can serve as a compromise, but requires that recipients check an additional social network.

**Sharing Motivation**
People choose to use social features for a variety of reasons. Many commercial applications, such as FitBit, gamify activity, such as by having friends compete against one another to see who can walk the most
steps. However, some groups within the FitBit community collaborate to reach a team goal.

Sharing socially can give the sharer a sense of accountability, such as resolving to lose weight [7]. Recipients can in turn provide social support by encouraging the sharer or suggesting ways to help them accomplish their goal. Additionally, the sharer may share a specific achievement or success. In this case, the sharer may be looking to receive praise or simply notify their recipients.

**Design Considerations**
Sharing motivation directly influences the kind of post that is made and the kind of feedback received. A system that is aware of users’ sharing motivations could guide the user to create posts that add to the activity descriptions (e.g., figures 1 and 3) by making the user’s intent in posting explicit. This could help users receive positive responses.

**Future Work**
While prior work has highlighted a number of points in this design space, very little is understood about what does or does not motivate people to share and respond to posts. To begin to answer this question, we are preparing a survey of experienced self-trackers to understand their positive and negative sharing experiences. We anticipate that people have particularly positive experiences when their posts receive substantial feedback, and are conversely disappointed when a post made receives no feedback.

**Workshop Participation**
We hope that this workshop will provide us the opportunity to discuss the different dimensions to consider when socially sharing this data. We hope that the other attendees will have experiences with and thoughts on socially sharing tracked data to share with us. While this submission highlights only a small fraction of the prior work in this domain, we want to learn about related literature from other workshop participants. Finally, the workshop will give us the opportunity to discuss design considerations with other researchers who are familiar with the space, and receive feedback on our opinions.

**Acknowledgments**
We thank James Fogarty and the HCDE 596 Directed Research Group on Technology Support for Health & Wellness for insightful discussions of these ideas.

**References**
How People Use Smartphone Apps to Manage Long Term Conditions

Kit Huckvale
Global eHealth Unit
Imperial College London
London, UK
c.huckvale@imperial.ac.uk

Cecily Morrison
Microsoft Research
21 Station Rd
Cambridge, UK
cecilym@microsoft.com

Abstract
Smartphone Apps hold potential to efficiently support those with long-term conditions monitor and manage their symptoms. Despite the availability of Apps, little research has been done around effective design approaches. We present initial findings of a qualitative interview study aimed to generate a rich account of how people with asthma and diabetes decide to use an app to manage their condition. We discuss App usage, personal data usage, and clinical data usage. We draw out different purposes for which the data is used and question whether the design should focus so specifically on the data itself rather than the collection process.

Author Keywords
Long-term condition management, smartphone apps, qualitative research, healthcare

Introduction
Long term health conditions, such as asthma or diabetes, require substantial self-management to maintain a good quality of life. People with these conditions are often encouraged to track their symptoms, or key data, in order to adjust medication and life activities accordingly. Smartphone Apps hold potential to efficiently support this type of monitoring. To this end, hundreds of Apps have been developed by companies and interested individuals. For example, a
survey of Apps to support the self-management of Asthma found more than 100. These include diaries for recording symptoms, treatment information, multimedia educational resources, and real-time sources of information like pollen and pollution warnings [3].

Despite the availability of Apps, little research has been done around effective design approaches. The equivocal results of several studies testing Asthma self-management Apps suggest that their design is not trivial [2,4,5]. To develop this design insight, a deeper understanding of the information needs of those who use Apps to manage long-term health conditions is needed. The purpose of the on-going study described in this workshop submission addresses this need. More specifically, its aim is to:

*To generate a rich account of how people with asthma and diabetes decide to use an app to manage their condition*

**Study Design**

Interviews have been carried out with people with Asthma or Type I Diabetes who currently use an App to support their self-management. Taking a contextual inquiry approach [1], participants were prompted to demonstrate with smartphone in hand how they used their App. The researcher then used this concrete discussion to probe related behaviors and feelings. To complement the narrative data, questionnaires were given to assess overall condition control, condition-specific quality of life and functional health literacy. Six-month follow up interviews are also being completed.

Fifteen participants were recruited through the local primary care network and on Facebook. A range of participant characteristics were sought to span age, gender, socio-economic class, and ethnic differences. Management of another’s care (e.g. child or spouse) was also included. All interviews took place in the participants’ homes or place of choice.

**Initial Findings**

An initial thematic analysis has been done for the first eleven interviews. We discuss three aspects of it which are particularly relevant to this workshop: App selection, Personal Data Usage, and Clinical Data Usage.

**App Selection**

The most common impetus for App usage was a crisis of some kind, a ‘critical moment’. For some this was a recognizable medical crisis (e.g. an emergency admission with pneumonia), for others it was disruption to an important aspect of their lives (not being able to pursue a main hobby because of poor condition control).

Substantial effort was not generally put towards App selection. Most participants went to their App store and made selections based on App descriptions and, sometimes, user feedback, looking for one that had the features they wanted (e.g. glucose monitoring). A few described a process of sampling downloads in which they tried Apps for a few days and then switched to another product. Only one participant described a systematic approach to App selection involving initial efforts to find online magazine reviews. While no participant was entirely satisfied with their current choice, each continued to use their chosen App.
**Personal Data Usage**

All participants appeared to have successfully established routine monitoring into their daily lives. It is notable that most were able to form and sustain daily monitoring habits (some for almost 12 months). This would be considered very unusual with paper diary keeping in which several weeks is usually the limit.

The routine interaction that people established with their app was limited when compared to what clinical self-management might consider as best practice. For some this was a strategic decision to focus on the collection of specific data, while for others, after an initial exploration of features, only a small subset was used regularly. Routine did not mean daily for all participants.

All Apps that the participants were using centred on objective monitoring activities (peak flow, glucose measurement + carbohydrates). Participants used these in a variety of ways. Sometimes the data led to quite specific criteria-based judgments for the day. For example, ‘I will not take the tube, because my Peak Flow is < Z.’ Participants also made judgments against trends at decision points, such as stopping a drug.

There was also a less decision-specific way of using the data in which participants made rough judgments about the state of their condition through a process of continual reflection against past data. For diabetes, this comparison involved reference targets (in line with clinical expectations of self-management). For Asthma, some participants expressed a looser sense of ‘knowing what was normal for them’. When questioned further, none was able to give a technically correct explanation of the measures’ meanings.

They had neither been given reference values by a clinician. Instead, they used phrases like ‘that just lets me know I’m keeping on an even keel’, ‘that was just a bit of blip’, ‘you can see it’s getting better all the time.’

One interpretation of this is that participants were deriving a broader meaning from the data about their overall condition rather than just using the data for day-to-day decision-making. It seemed that an important function of the data beyond decision-making was to provide some reassurance about their condition. This came through most clearly for those who had to manage and try to achieve control over an unpredictable condition. In one case, it seemed that having control over these numbers helped compensate for a wider sense of loss of control in a case where there were multiple unexplained medical issues and profoundly limiting disability. Yet, we also saw cases in which the process of collecting data was used to provide that sense of control rather than responding to the problematic numbers.

**Clinical Interaction Data Usage**

While no participant started using an App as part of a clinical intervention, there were examples of data usage to mediate patient-clinician interactions. We found examples of both positive and negative interactions. To the positive end, patients brought, unprompted, data to their managing clinician to discuss treatment options. It was unclear whether the data was useful, but some participants gave a sense that this was one way to demonstrate being “a good patient.”
In contrast, one participant used her data to argue with the clinician to take her condition more seriously. The clinician did not feel her symptoms were Asthma related, but she was able to demonstrate this through changes in her peakflow data. This contrast suggests that the use of data can play to the patient-clinician interaction in different ways, not necessarily intended by either policy makers who propose Apps as a mechanism of self-management or proponents that Apps can liberate people from the constraints of the clinical relationship [6,7].

Discussion
The initial findings of this study suggest that there are at least some people who are managing to use an App to support their self-management strategy over time. However, we were surprised by the constrained nature of the interaction. We have termed it satisficing. There were limited attempts to find the 'best' app; feature use was minimal and often rationalized over time; and shortcomings overlooked.

Participants had developed some expertise in interpreting their data and conducting monitoring, but this was largely bounded by their initial choices and understanding of measures used in their condition. Behaviors for those with diabetes were more closely aligned to clinical expectations around glucose and carbohydrate, perhaps because of their proximate role in avoiding symptomatic hypo/hyper-glycaemia by choosing insulin dose. For asthma, however, there is a greater flexibility around medication taking to manage symptom experience: the scope for satisficing is probably greater. Perhaps most interestingly, there seemed to be multiple uses of the data. Not only were people using trend data for decision-making, but many it seemed that the process was as important as the resulting numbers. Reflection on this finding suggests that there may be other motives for data collection, then direction management of symptoms.

We offer this initial analysis to raise questions about what we should be designing for in an App to support self-management. Is it enough to focus on convenient data collection and the trade-off of quality versus collection time? Or, do we need to consider more broadly the role of these Apps for both personal use and as part of the clinical encounter?

References


What’s Next for Quantified Health: In-Context Decision Support for People with Chronic Conditions

Abstract
A growing number of people are living with chronic conditions, and tracking data about their health and bodies on a daily basis. There’s an opportunity for the Quantified Self movement and future self-tracking solutions to not only help this population more effectively monitor and manage their conditions, but to provide real-time and in-context decision-making support for improved health and lifestyle outcomes. Designers will need to address unique requirements for people living with chronic conditions, as well as open issues around privacy, instinct, identity, and attention.

Author Keywords
Quantified Self; Self-tracking; Chronic Conditions; Decision Making; Medium Data

Introduction
60% of adults in the U.S. track a metric about themselves, such as diet, weight, or exercise; at the same time, 33% of adults in the U.S. track health indicators or symptoms, like blood pressure and sleep patterns [5]. With a growing number of wearable computing devices [1] and health-focused apps [9] available today, self-tracking has moved beyond medical and athletic domains and entered the mainstream. The Quantified Self is no longer an aspiration limited to a special interest group, but one

Nikki Pfarr
Research Lead
Artefact
225 Terry Ave N., Suite 300
Seattle, WA 98109 USA
nikki@artefactgroup.com

Matthew Jordan
Research Director
Artefact
225 Terry Ave N., Suite 300
Seattle, WA 98109 USA
matthew@artefactgroup.com

Dave McColgin
Research Director
Artefact
225 Terry Ave N., Suite 300
Seattle, WA 98109 USA
dave@artefactgroup.com
that is relevant to an expanding segment of the population.

However, while people have access to more data about themselves than ever before, it’s unclear to what extent these data play a role in motivating and maintaining behavior change. It’s possible that for many people these personal data sets do little more than fulfill a natural self-curiosity, and that the promise of the Quantified Self as a route to improved health and lifestyle dissipates as the novelty of tracking wears off.

It’s time to push the boundaries of the Quantified Self movement beyond simply making self-tracking more accessible and toward helping people take action.

A call to Action-Taking
In [11], Swan describes four functional layers for the Internet of Things: Data Acquisition, Information Creation, Meaning-Making, and Action-Taking. These layers are relevant to the subset of "things" that help us track and monitor biometrics and other personal data.

The Quantified Self movement has generally been stalled in the Information Creation layer of this framework, and is just beginning to move into Meaning-Making. Action-Taking remains largely unaddressed by the Quantified Self movement to date. We argue, however, that transforming data into actionable insights is necessary for improved long-term wellbeing and health outcomes. People don’t just need to understand the data they’ve collected, they need to know what to do next.

Action-Taking can be done in two ways: helping people initiate and complete planned action (achieving health-related goals over time), and providing decision-making support in real-time.

Data, decisions, and chronic conditions
Transforming data into actionable insights could especially benefit the growing population of people with chronic conditions. By 2030, an anticipated 171 million people in the U.S. will have at least one chronic condition, an increase of 36.8% since 2000 [8]. People with chronic conditions are more than twice as likely to engage in self-tracking as those without chronic conditions, and are more likely to update their data more regularly [5].

In addition to handling large volumes of data, people living with chronic conditions are making a range of daily decisions that may impact their health outcomes – such as what to eat, how much medication to take, and when to administer self-tests. When these decisions require making a choice that favors health, but conflicts with what a person really wants to do (e.g., choosing a salad over chips), it can result in the depletion of resources necessary for self-regulation (known as ego depletion, see [2]). This depletion of resources can impact a person’s ability to make subsequent “good” choices moving forward. The presence of psychological conditions like depression result in additional challenges due to misregulation, where “the successful management of one condition conflicts with the successful management of the other” [3].

Turning data into real-time and in-context decision support has the potential to reduce cognitive burden for
people with chronic conditions, help them cope with misregulation, and improve overall health outcomes.

**Added data for real-time decision support**

Though people living with chronic conditions may benefit from real-time decision-making assistance, the power of making recommendations based on individual datasets assembled through self-tracking may be limited. Fortunately, a growing number of external datasets are available online, particularly as a growing number of objects and spaces become sensor-equipped and internet-connected [4]. These “things” lend to the creation of a "passive background layer of continuous monitoring that could be helpful in improving physical and mental health” [11].

By pairing data collected by connected things in a person’s environment with data gathered via self-tracking, as well as relevant "medium data" (e.g., data from populations with similar characteristics), we can uncover new correlations and make more informed, real-time recommendations. This powerful amalgamation of data could yield new insights and predictions about a person’s likely behavioral, emotional, and physiological outcomes. See [11] for a similar idea, the "Biometric Recommendation Engine."

**Design requirements**

As the Quantified Self evolves to focus more on the needs of people with chronic conditions, several unique design requirements will need to be met:

*Fit into users’ daily lives (non-clinical environments)*

People living with chronic conditions deal with monitoring and management in a wide variety of environments – from homes, to outdoors, to crowded public spaces. Medical devices and interventions, however, are typically optimized for use in hospitals. Patients are forced to invent awkward workarounds for these products, increasing burden of use.

*Be accessible to non-experts*

Care increasingly takes place outside the doctor’s office. Patients and family caregivers must be able to understand and use new solutions. At the same time, people’s expectations about how technology functions are increasingly influenced by mainstream consumer products; these expectations shape their interactions with medical devices and interventions.

*Help users “cut through the noise”*

People living with chronic conditions are handling their own personal data, along with a wide range of health information available online. It can be difficult to decide what to focus on, and what should be ignored.

*Maintain continuity of care*

Most patients with chronic conditions see several clinicians [8], and that number is growing with the rise of retail clinics [7]. This can cause continuity of care to break down. New solutions can help maintain continuity across providers, e.g., by keeping providers up-to-date, making data easy to export and share, and helping users track and reconcile different recommendations.

*Enable a range of care team participation*

Medical practitioners can contribute domain expertise and valuable knowledge of a patient’s medical history to new systems, and also need to remain informed about a patient’s status. However, time constraints and varying degrees of enthusiasm for consumer products suggest the need for flexible engagement models.
Additional considerations
In addition to the preceding design principles, there are several "open issues" that require further investigation:

Privacy expectations
What are users’ privacy expectations when it comes to sharing personal data and medical information with others? As people share a growing amount of personal information online, privacy expectations are in flux.

Personal instincts versus numerical data
Is an emphasis on numbers and "quantifying" the self diminishing the importance of listening to one’s body and trusting personal instincts [6]? Could a reliance on data prevent people from thinking for themselves?

Perception of identity
How does the concept of the self change as the body becomes enhanced by and supplemented with technology? How do self-tracking and monitoring devices impact identification with a larger population, patient or otherwise?

Attention to the body
As suggested in [6], self-tracking may make the body more 'visible' to users, for better or worse. Could self-tracking make patients with chronic conditions more acutely and continuously aware of their conditions, or might it help them offload the burden of monitoring?

References
Empowering people to test their own quantifiable hypotheses with pervasive displays

Abstract
Lifestyle diseases may result from inappropriate personal behavior such as poor diet, smoking, alcohol and other drugs, or lack of exercise. Modifying behavior may be all that is necessary to prevent the disease. We believe that pervasive logging and awareness interfaces can be useful for maintaining long term efforts to modify behavior and enhance health by enabling people to evaluate personal quantified hypotheses. We aim to explore which classes of interfaces are most effective for this.

Author Keywords
long-term health and well-being; personal hypothesis; pervasive; diet; nutrition; persuasive.

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

Introduction
The growth of so-called life-style diseases in western society is related to diet and physical activity. The changes that have occurred with industrialization and market globalization have led to inappropriate patterns of diet, reduced physical activity and a corresponding
increase in chronic diseases [13]. Examples of negative diet patterns are inadequate intake of vegetables and fruit, over consumption of sugar-sweetened beverages and high-fat foods [8].

Our approach to these long term health challenges is to enable people to formulate and test personal hypotheses. Our definition of a personal hypothesis is an individual’s belief about the ways their actions affect their lives. Providing access to pervasive touch screen interfaces helps people to log and see the information about the status of their personal hypotheses. We believe this will lead to a change behavior toward their goals for health and diet. We use the notion of means and end-goals to define a personal hypothesis. For example, a person might believe that if they can see and log their intake of fruit each day (means-goal), this will improve their health (end-goal).

We aim to enable people to evaluate personal quantified hypotheses (see side bar). Ideally, we should be able to measure A and B in a convenient and unobtrusive manner. Currently it is difficult to achieve this for many behaviours. For example, food intake requires considerable effort for people to record. We aim to address this using pervasive displays embedded in homes to readily capture this type of data. In our experimental system we capture data such as the number of serves of vegetables consumed by logging this on a small dedicated touch screen mounted on the bathroom wall near the toothbrush. The location of these displays is important. Mounting it in a location that is visited at a regular time makes it more likely that the user will notice and interact with it.

Our scenario is about Alice, a person whose goal is to change to a healthier lifestyle by eating enough fruit each day. She wants to use a device in her bathroom near her toothbrush and a similar one on her desk in her office. The number of serves she had eaten each day will be displayed on the device, and she will be able to log the amount of fruit intake, when she eats some fruit.

**Related Work**

There is a body of work on awareness systems for behavior change for health. For example mobile phone text messaging has been used in studies such as [2, 4, 11, 12] for medication, prevention of disease and health behavior change. There are also many mobile applications, websites and devices which have been developed to help people maintain and change their behavior. These studies showed that just reminding people, for example with a SMS, help a lot in achieving their goals.

Moreover, pervasive awareness interfaces, such as calm and ambient displays have been used for influencing people to make positive behavior changes. These interfaces are capable of bringing previously inaccessible information to one’s attention. The presented knowledge can be interpreted with just a glance. Breakaway [5] is an example of such an ambient display designed to encourage people who sit for long periods of time, to take breaks more frequently. It is a sensor-driven ambient sculpture which gets information from the user’s chair and suggests when the user needs to take a break. Breakaway’s four original design goals are abstraction, non-intrusiveness, public, and aesthetic. Its initial
evaluation showed positive changes in behaviour of the users.

Consolvo et al. [3] propose design strategies for persuasive technologies that help people to change their lifestyle behaviour. They argue designing such technologies is complex and need a set of strategies. They started with the four strategies considered in Breakaway and come up with the set of eight strategies: 1) abstract and reflective, 2) unobtrusive, 3) public, 4) aesthetic, 5) positive, 6) controllable, 7) trending/historical, and 8) comprehensive. They also validated these strategies in their field studies and noted that these strategies are not meant to be mutually exclusive and can overlap at times.

Clinicians and researchers in health use techniques such as food diaries [9, 10] to understand what people are eating and measure their food intake. It has been shown that mobile digital diaries are more helpful to observe and self-reflect on eating habits, as it is easily accessible and can show the amount of foods consumed.

The quality of food intake can be measured by the amount and types of food eaten. There have been a number of scoring systems [6] to calculate the quality of diet based on the core foods that must be consumed more and the restricted items which required being limited in intake. Core foods are those identified as nutrient rich and has been categorized into five food groups of: 1) fruit, 2) vegetables, 3) dairy, 4) meat, fish, poultry, eggs, nuts or legumes, and 5) bread, grains and cereals [8]. The restricted foods are in low nutrients and high kilojoules. These energy-dense nutrient food groups should be restricted. The amount recommended for each group is specified in the Australian Diets guidelines [8] based on gender and age. The Healthy Eating Index for Australian scoring system was designed by Allman-Farinelli [1], informed by two dietary scoring systems developed in the US. She demonstrated that this diet scoring system predicted the odds of cardio and cerebro vascular disease in a cohort of 1790 participants.

**Design**

In our design of our proposed logging and awareness interfaces to improve health, we consider the design strategies for persuasive systems to help people change their everyday behaviour. For example, the data which is presented to the user needs to be abstract, pleasing, positive and consider privacy issues.

As a part of personal hypothesis exploration infrastructure, our goal is to build interfaces for logging and displaying the food consumption in order to achieve health and well-being goals for a healthier diet.

We plan to place small touch screen displays in convenient locations around the home and office. These devices will be special purpose: dedicated to logging behavior in a single domain for a single person. Members of a family can have their own displays, located side by side and see their own data. The display and interaction is very simple and easy to use: a single tap on a square will increment a count with feedback given below the category and the colour changing when a goal is reached (e.g. Figure 1). The display resets to the initial state at midnight each night.

The data from these touch events is sent to a back-end server and entered into the user’s personal datastore.

---

**Figure 1.** Pervasive touch interface mounted on bathroom wall. (Implemented using a low-cost smart phone)
where it is available to a dashboard application and other applications. The dashboard application, Mneme [7], was designed to support the user in key tasks: defining their own goals using terms of their choice; linking personal goals to pervasive computing sensor applications as they wish; linking in other applications they choose to provide additional services. The services could be notifications and reminders (e.g. congratulations on reaching your goal!), or ambient displays such as an orb that changes colour depending on personal performance.

Conclusion and Future Work
Modifying behavior is the goal of many people when treating lifestyle diseases. We are currently prototyping pervasive logging and awareness interfaces that will be used for maintaining long term efforts to modify behavior and enhance health by enabling people to evaluate personal quantified hypotheses.

References
I Am Not a Patient: Design Challenges in Self-Screening Medical Devices

Abstract
Personal health informatics refers to a type of medical systems and devices intended to be used by users without professional medical training. They play an important supporting role for healthy decision-making in non-clinical environments. There are two important categories of personal health informatics: self-monitoring and self-screening. Self-monitoring devices help users better manage illness and maintain wellness through surveillance of health parameters, which has been widely studied in recent years. However, self-screening medical devices, of which the users are unaware of their potential illness, are less understood. This paper presents the first results from an investigation into the difference between self-monitoring devices and self-screening devices. Based on a skin cancer self-screening mobile system, we conduct semi-structured interviews to explore the challenges regarding acceptance and adoption. Future work that focuses on addressing the design challenges evolved are also introduced.

Author Keywords
Personal health informatics; self-screening; acceptance and adoption; interviews;

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

As life expectancy rises, the prevalence of health problems is expected to increase [8]. With this, the cost of supporting the related healthcare ecosystems would become a serious social burden. Personal health informatics systems have the potential to help mitigate this financial and social tension [5]. Through presenting analytic interpretations of users’ health data, such systems enable users to detect and interpret early disease symptoms, be aware of their health condition and support healthy behavior changes by linking to long-term health objectives.

While researchers have paid increasingly attention to both patients and doctors’ needs [2] to identify the design requirements of personal health informatics system, one type of such systems are less studied so far- the systems that assist users to perform self-screening. The users of these systems are not identified as patients yet. This user category presents unique acceptance and adoption challenges compared with users of other personal health informatics devices. For instance, it is not clear how to incentivize usage, how to best present results, and how to sustain habit formation for periodic long-term use.

Self-monitoring Vs. Self-screening

Self-monitoring devices collect physiological parameters through wearable or non-wearable sensors or journaling forms [7]. The users defined in this context tend to have received professional medical diagnosis, being categorized as “patients” or at least are aware of the problem (e.g., obesity or diabetics). By providing this type of users own personal health information, researchers aim to empower them to take an active role in their health management [6]. In contrast, self-screening devices work as an accessible pre-screening method to help users to identify potential health problems in the early stages of the diseases. Before being formally diagnosed with a particular health problem, the users have different considerations and needs compared with “patients”. In addition, although self-screening devices requires a routinely data acquisition like self-monitoring devices, a large number of them are usually designed without a long-term health objective which could encourage healthy behavior changes. Instead, these systems typically provide a yes-no suggestion or risk assessment of specific diseases. We argue that lacking long-term health objective may also cause difficulty to sustain usage of the devices. An example of self-screening device from our prior work is briefly introduced below.

eSkinCheck System

Skin cancer is one of the most common cancers in Caucasians. Due to the lack of patients’ awareness, the presence of disease is diagnosed by doctors only at a late stage, usually fatal by then [4]. Aiming to assist people to diagnose the risk of skin cancer in a low cost and timely, we develop eSkinCheck system [9], a mobile-based self-screening application for providing common users early detection of skin cancer.
To carry out the self-screening, users need to capture the skin lesion area using eSkinCheck. Then the system uses image analysis to compute features that capture the morphological and chromatic characteristics of the skin mole. Based on these features, the system uses machine learning based algorithms to estimate the malignancy and to provide suggestions (Figure 1).

Acceptance and Adoption Challenges
To explore the design issues of self-screening systems, we conducted semi-structure interviews with eight older users (over 65 years old) using the eSkinCheck system as an example. We illustrate the interview insights based on the acceptance and adoption of the technology.

Acceptance
Users raised questions about potential harmfulness as a first concern—despite our system being implemented on a smartphone. Older adults may associate these systems with the hospital diagnostic machines and question about whether risky detection methods (e.g., “X-Ray”) would be used, even among the older adults who had used smartphones for a long period.

The older adults also expressed high system acceptance if expertise of the diagnosis could be verified. Some interviewees expressed they may start to use the system only after receiving the recommendations from their peers.

A key viewpoint expressed by some interviewees is that they intend to keep happy without being aware of any potential disease, even if this would heavily threaten their health in the future. The designers of self-screening systems should investigate how to turn the sense of negative disease detection into the notion of positive health maintenance.

Adoption
In order to detect the potential risk of disease timely, the self-screening device requires routinely usage. Thus, we also explore the long-term adoption of the device in the interviews. Apart from the easiness to use, older adults expect the results of the diagnosis to be easy to understand. The detailed analysis of personal health data was considered confusing and complex.

Without a specific long-term goal like self-monitoring device, the motivation of sustained usage is a key challenge. Most of the interviewees reported they would not continue to use after received negative results several times. However, they still expressed the need for regular formal medical check-ups. Thus, the reminder of self-screening may help routinely data acquisition, especially in the case that the reminder was from a professional, as some interviewees suggested.

It would be helpful to keep the data acquisition in a routine if the process is performed by family members or potential care givers. However, the older adults indicated that they only intend to "trouble" the family members if they have a good relationship.

Future Work and Discussion
Our work suggests that a novel type of personal health informatics systems need further understanding of users’ needs and perceptions. From our interviews, we identify three unique issues of self-screening devices: the importance of less "perceived harmfulness", the difficulty of sustaining usage without a long-term goal and the lacking of intention to learn negative personal
health information. We acknowledge that the culture difference may exist towards the system usage. However, we believe that the difference is more subtle than argued regarding the issues we have explored. Our future work will further design our current eSkinCheck system by embracing the end users’ considerations and conducting field studies. More specifically, we will consider:

**Belief** - Previous research reports that acceptance of medical ICT devices is strongly motivated by perceived usefulness [3]. Moreover, in our context, we aim to design self-screening systems with low “perceived harmfulness” and high “perceived expertise”.

**Beyond Yes or No** - Arnrich et al. suggest shifting the reflective disease management to a more pervasive and assistive focus [1]. Future work will investigate how to embed the pervasive information with a constructive health objective into the simple diagnosis information, thereby improving sustained motivation.

**Positive Perspective** - Users should not be “scared” by the perceived negative disease-diagnosing behavior. Future design will focus on how to present disease diagnosis process in a positive health maintenance way.

**Reminder from Doctors** - From our interviews, reminder helps keeping the motivation of sustained usage, especially if the reminder message is designed in the form of professional doctors’ narratives.

**Acknowledgements**
The material reported in this document is supported by the SUTD-MIT International Design Centre (IDC). Any findings, conclusions, recommendations, or opinions expressed in this document are those of the author(s) and do not necessarily reflect the views of the IDC.

**References**
Community Level Health Data: Looking at Real-Time Dating Sites

Mark Handel
(The Boeing Company)
Seattle, WA
handel@gmail.com

Irina Shklovski
IT University of Copenhagen
Copenhagen, Denmark
irsh@itu.dk

Abstract
We discuss the potential for a new source of data for personal health maintenance, community-level data sourced from a variety of social networking sites. We present some preliminary results on extracting this kind of data from dating sites catering to men who have sex with men (MSM), and discuss possible user communities for this information.

Author Keywords
Community Health Sensors; MSM; HIV; Real-Time Dating Sites

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

Introduction
Most of the research in the quantified-self movement has focused on individual level data, which can be used to improve health and well-being. These data points have the advantage that they are acquired and reported by the individual who is the direct user of the relevant devices, and there are only “classical” privacy concerns within the data ecosystem: who has access, how are the data summarized and aggregated, and so forth. However, self-reported health information and quantification of self does not necessarily have to be
limited to the use of particular devices (such as FitBit for example) or mobility tracking services (such as Strava). As sharing of health information becomes more normatively acceptable, it is likely we will begin seeing certain types of information disclosed on regular social network sites or dating sites. In fact, this is already happening in certain niche communities, such as among men who have sex with men (MSM) where particular types of health information, such as HIV status – can be vitally important in the context of interaction and especially dating. However, data obtained from such sources as online dating profiles comes with a different issue – dating profiles tend to be exceedingly stable and thus the health data can be significantly out of date [1]. Yet we argue that these kinds of data, nevertheless, can provide a relatively accurate measure of community-level data. We discuss some of our preliminary work in a novel area, but one that has fairly important health implications, at least for the members of the specific community under study.

We have been studying real-time dating sites (RTDS) [1], including, but not limited to location-based systems (e.g. Grindr and Scruff) and websites (e.g. Manhunt and Gaydar). These online dating sites are primarily geared towards MSM, and although there are a range of sites, including mobile apps, most of them have a core set of features: individual profiles, an “online now” indicator, geographic restrictions, as well as a messaging infrastructure. Within the MSM community, some of these sites and apps are very popular (we will refer to them generically as sites): the biggest of the mobile apps have over 1M active users, and the web sites can also boast a similar reach. With such a wide user base, there are obviously differences in goals and usage patterns; some people use them for casual sexual encounters, while others seek more of a community orientation even when using products that support new social interactions [2].

**Dating Sites as Data Sources**

The dating technologies popular in the MSM community are interesting from a well-being standpoint because they act as a new source for certain types of health information. Although this information is generally about an individual user, we want to focus on the potential for using this data as a community-level indicator or sensor for important health-related information. This is an area of emerging interest, for instance, recent work has explored the potential of Craigslist for providing sensors for sexual-health related content in personal ads [4]. These sites gather a wide range of both self-reported and implicit data about their users. The self-reported data often includes the expected questions about age, weight, height as well as drinking and smoking but also items more specific to this community, such as personal HIV status, potential partner HIV status and drug use information. Obviously, self-reported data has significant limitations and biases, but many of these biases are relatively well understood, for instance, weight is often under-reported especially on dating websites.

In addition to these self-reported data, there are also large amounts of implicit data that are generated by individuals’ use of these products. These encompass such things as temporal patterns of usage, short or long-term absences from product usage, as well as overall intensity of usage. These can be collected both on an individual level as well as aggregated across varying levels of community. In addition, there is the potential to examine various kinds of communities:
geographic distribution is an obvious contender, since this is how many of the products are structured, but there is also the potential to cluster on other relevant factors, such as age, HIV status or drug use.

Through our work we have found that both classes of data are, within the terms of use restrictions, relatively easy to gather and process. We have used the data gathered to look at the potential for creating these sensors. We will look at some potential designs, and then discuss how these sensors could be deployed to a variety of stakeholders: both individuals and organizations.

**Our Work**

We have been examining data collected from these sites to look at three potential community-level signals: HIV status, drug use, as well as overall usage intensity. For the MSM community, HIV status is obviously a very important indicator for health and well-being. However, HIV status is not necessarily the dichotomous variable it once was. Modern HIV treatment regimens can bring the viral load down so low as to be undetectable, which greatly reduces the risk of transmission. More recently an increasing number of HIV-individuals have begun taking a Pre-exposure Prophylaxis regimen (PrEP), which can also greatly reduce the risk of transmission. Thus, just saying positive or negative is no longer necessarily enough to fully capture the range of risk. In addition, research has shown that individuals who are not aware of their HIV status are often the biggest source for new HIV infections [5]. This has led to a new push for regular testing among sexually active MSM. Although most of the sites under study have controlled vocabulary fields and drop-down menus to indicate HIV status at varying levels of granularity almost none have a formal “Recent Test Date (RTD)” field. Nevertheless, we have been observing and increasing number of users putting dates of their last test in the free text sections of their profiles.

In addition to HIV status, another major impact to overall health is the rate of drug use. Although most sites list this as “drug use,” in practice, this is usually understood to mean methamphetamine use, a popular drug in the MSM community (It is not unusual for a profile to say no drugs, but also indicate openness to “softer” drugs like marijuana.) Like HIV status, drug use status is often a mixture of controlled vocabulary fields in the profile, mixed in with additional details in free-text profiles.

We have been looking at ways to aggregate these disparate pieces of information, which can be missing, incomplete, or inaccurate from the profiles, and using it to give an overall metric of certain health aspects of a community. Much as vaccination can provide for herd immunity, many of the HIV and drug use harm reduction efforts can also provide for increased overall risk reduction.

We are still exploring the design space, in terms of aggregation and presentation of this data, as well as exploring how users will react to this kind of information. In figure 1, we show a graph of HIV prevalence over time in two different cities. Another possible visualization is to cluster results along other factors, such as drug use, as seen in Figure 2. (Unfortunately, in this instance, there is only a 2% difference between the two populations)
Discussion and Future Steps

These sensors can be used by individuals to get a better sense of the community they are interacting with. This information can be used to help them moderate their own actions, or to provide prompts for discussion before initiating intimate contact. In addition, they can also be used by community health advocates to understand areas for outreach and interventions. For instance, if the average time since the last HIV test is growing, additional testing opportunities can be scheduled.

One obvious area of concern is anonymity in this data. In our examples, we have been careful to only present data at a community level; most of the results are the combination of hundreds of individuals over many sampling points. However, it would be interesting to discuss these kinds of sensors with users of the sites. An interesting tension that may arise is that, individually, all of this data comes from “public” data on the site: this is information that is present in their profiles, and visible to all of the other users of the site. However, the aggregation may be the source of concern, even though it is less identifiable than the individual profile data.

Bibliography


Abstract
This paper discusses ideas and opportunities for the use of mobile phone app launch log data in the understanding and improvement of health and wellbeing. Rather than analysing a phone’s sensor data or specific user actions within an individual app, the data set we discuss concerns when apps are launched on a mobile device and the duration of usage of each app. This data gives an abstract but broader picture of how a mobile device is used. Since many people use such devices regularly throughout the day, we suggest that such data can help build a useful picture of day-to-day activity. We also suggest it is helpful to look not only at health and wellbeing apps individually, but at how these are combined and used over the long term.

Author Keywords
Health and wellbeing; personal informatics; tracking

Introduction
There has been much interest over the past few years in mobile applications and devices for health and wellbeing, including applications that track activity (such as pedometers) and applications that enable the user to log activity (such as food loggers). In this paper we will suggest looking beyond sensors or individual health-related applications and to how the mobile
device as a whole can serve as an indicator and facilitator of health and wellbeing.

We will use the term app tracking to mean the recording of every time an app is launched on a mobile device, along with its duration of use. Our key premise is that app tracking can underlie new innovations in this area for health and wellbeing. The ideas we present in this position paper are speculative and forward-looking. They are grounded in our experiences in such logging (which include the release of a logger for iOS that has, to date, been downloaded over 25,000 times) alongside our experiences in developing applications for health and wellbeing. However, with this paper we seek to look beyond our current studies, and to envisage new directions for ‘the quantified self’.

App Tracking
While there has been much discussion and innovation based on in-app logging in health and wellbeing (i.e. the developers of an application logging and storing data on how their particular app is being used – e.g. [1]), the use of app tracking in this area is relatively unexplored. Whereas in-app logging concerns what is done in an individual app, app tracking concerns what is done more broadly on a device. Such logging is not the combination of two or more in-app logs, but rather presents a more abstract way of considering how apps are used. Primarily, an app tracking log can include when each app is opened, when an application launcher or device home screen is used, when the phone is locked or unlocked and when the phone sleeps. Other information that can be collected includes connectivity, battery state, charging state, and location. We describe our approach to app tracking elsewhere [2], including the ethical considerations. Other studies that draw upon this type of logging include [3]. The example log in the margin of the following page shows a pseudo log to illustrate the kind of data we are describing. This is simple data giving minimal information about what is done on the device. Yet, as we will explain, it can potentially be used to supply insight into health and wellbeing.

App Use Logs as Proxy for Behaviour
Mobile devices are used frequently throughout people’s waking hours. This means, as figure 1 shows, that for many users it is possible to obtain a reasonably good idea of when they are sleeping. We have found many people use their mobile phone last thing at night and first thing in the morning, often as an alarm clock. People will often also reach for their phones if awoken or having difficulty sleeping. Participants in our studies have been struck by how obvious their sleep patterns are when shown visualisations of their data, with some reporting that limited or interrupted nights of sleep were more readily visible from our data than that gathered from dedicated wrist-worn trackers.

The use of the phone is also patterned during the day. These patterns are far more complex than the blank periods we often observe at night, but we suggest there are opportunities to explore these. It may or may not be possible to differentiate a ‘sick’ day from a ‘normal’ day but it is reasonable to envisage connections being made between patterns of app use and patterns of activity.

Logs as Proxy for Mental Wellbeing
Links have been shown between the social connectedness of people and their physical or mental wellbeing (e.g. [4][5]). Reduced social engagement is
sometimes an indicator of deterioration of mental wellbeing. Madan et al [4] inferred participant health status using a combination of Wi-Fi scanning to detect movement, Bluetooth proximity to detect face-to-face encounters and call and SMS logs. It would be interesting to study similar issues solely through the study of social apps or services. App tracker logs do not enable the collection of data about face-to-face meetings, or specific social connectivity (e.g. who is called on the phone), but do allow for analysis across apps, to look for fluctuations in the use of communication or social networking apps in general.

Alternatively, it can be considered that people often feel their phone is addictive or something that moves them away from social life. People may wish to use a personal informatics app in order to gain more control over their device use. The use of app tracking logs simply to feed back information about when and how often the phone is used may be a useful step in gaining a sense of control, and help become more mindful.

Tracking Across Apps

App tracking logs may appear to offer less insight into health or activity than the data gathered from an individual app. But we should consider that health and wellbeing apps are not always used individually, but in sets or as ‘configurations’. In our experience, many people do not just use one health app, but several. For example we see a lot of people using diet apps such as MyFitnessPal as well as pedometer apps. People also sometimes use several exercise apps, for example separate apps for gym exercise, for running, for cycling, for swimming. We should be mindful therefore that if we are to look at app use outside of controlled studies we need to look across apps.

Secondly, we should consider that health and wellbeing apps are often not used indefinitely. Applications often seem to be designed with the idea that users would consider that the more data is gathered, the more valuable it becomes. Yet through our studies we have found that many people will often use several different applications over a period of time, perhaps switching from one pedometer to another. Moreover, we have noticed that users are often keen to get a good sense of their routine, but once they know how many steps they typically take walking to work or the distance of their favourite regular cycle, that collecting data becomes less useful. App tracking at a large scale with many thousands of users allows us to look across such long term use of apps, in particular allowing us to look at when apps are switched between, the patterns of trying out and sticking with apps, and whether one app tends to be replaced by another, or users stop using a particular class of app altogether.

Example Log

Below is a pseudo log illustrating the kind of data we are discussing. It simply shows the time an app is opened or the time a phone is locked/unlocked. The log should also contain the date, and the expectation is that logging would be over weeks and months.

01 17.30.00 Unlock
02 17.30.05 Strava
03 17.30.05 Lock
04 19.00.00 Unlock
05 19.00.01 SMS
06 19.00.06 Launcher
07 19.00.10 MyFitnessPal
08 19.07.10 Jawbone
09 19.00.10 MyFitnessPal
10 19.00.30 Strava
11 19.00.10 MyFitnessPal
12 19.02.00 Launcher
13 19.02.05 Lock
14 21.00.00 Charging On

Figure 2: A Plot showing minutes of device use for every hour of one day. What is most apparent is a blank period, strongly indicating when this person slept.

Beyond Quantified Self: Data for Wellbeing 28 Workshop at CHI2014
Design Opportunities
We have alluded to several design opportunities:

- Sleep tracking
- Analysing patterns of behaviour
- Analysing social connectedness
- Managing excessive app use
- Understanding the use of multiple apps
- Understanding long term patterns of use

Firstly, we should address why anyone would consider using app tracking data as a proxy for behaviour when high quality trackers are already available. The answer is that doing so uses ready-existing information. It does not require an extra device or app to be running which could have a high battery cost.

Secondly, we should address that app use data may well compliment rather than replace other health and wellbeing data. For example, it is interesting when data from an activity tracker is viewed alongside these logs. This information often reveals the phone is used when sedentary, and that game-playing is associated with long periods of physical inactivity. Contemporary health research is pointing to the importance of reducing sedentary time [6], yet sedentary behaviour is hard to track because it is difficult to sense light movement, and sensing across the day can have a cost on battery. We think turning to the kind of data we describe could help in looking beyond tracking active behaviour to the challenge of understanding sedentary behaviour.

Finally, we believe it is important to move beyond thinking about individual apps for wellbeing and behaviour change. We do not believe behaviour change needs to be, and foresee that it rarely will be, achieved using an individual app over the long term. We think a challenge for this area is in understanding how people work across and between different apps over the long term. App tracking can help in understanding this.

Conclusion
This position paper has discussed opportunities and ideas regarding 'app tracking' and health and wellbeing. The paper is speculative, arguing that the future of 'the quantified self' may lie across and between apps. This is not to say the future is in the rational integration of data, but to say it is in understanding and making use of the messy and patchy ways in which mobile devices are used in the real world.

References
There is More to Well-being than Health Data – Holistic Lifelogging through Memory Capture

Tilman Dingler
University of Stuttgart
Stuttgart, Germany
tilman.dingler@vis.uni-stuttgart.de

Alireza Sahami
University of Stuttgart
Stuttgart, Germany
alireza.sahami@vis.uni-stuttgart.de

Niels Henze
University of Stuttgart
Stuttgart, Germany
niels.henze@vis.uni-stuttgart.de

Abstract
With the recent wave of commercial sensing devices such as Fitbit step counters, Lark sleep monitors, and the Withings scales, the quantified self movement gained quite some traction. With Electroencephalography (EEG), eye trackers and document retrieval algorithms it is even possible to track mental activities such as reading. The wide range of available sensing technologies and their increasing pervasiveness allow us to draw a holistic picture of a user’s activities. In this paper we describe explicit and implicit approaches that we currently use to track physical and mental activities and to record memory. We conclude with a summary of open discussion points about the approach and feasibility of logging such holistic life data.

Author Keywords
Memory; quantified self; capture

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

Introduction
Thanks to the ubiquity of smartphones and the rise of available, wearable technologies, large-scale data collection has become very popular. People log their daily...
steps with commercial products such as *Fitbit*\(^1\) and keep track of their activities and locations using apps like *endomondo*\(^2\). Gordon Bell [1] went even further and made it his mission to attempt to record his entire life: images, sounds, videos as well as personal documents. He pioneered the trend towards lifelogging applications that has been supported by research projects such as Microsoft’s *SenseCam* [2]. Whereas technologies such as *Fitbit* are aimed at collecting quantitative data about movement and health to set incentives for improvement, the *SenseCam* serves as memory aid by automatically capturing a digital record of the wearer’s day.

Further, attempts have been made to recognize activities, such as walking, running or sleeping by making sense of smartphones’ accelerometer data [3]. The quantified life is not limited to only physical activities though. Kunze et al. introduced a system that used eye tracking in combination with image retrieval techniques to track what and how much people read in their daily lives, thereby creating the *wordometer*\(^4\). Kunze describes this development of tracking such activities for the mind as the ‘trend towards a cognitive quantified self’.

Taking together the logging of physical and mental activities and combining them with a life log of moments and memories we are getting closer to a holistic quantified self. In our work we investigate such a holistic approach to strengthen and augment human memory. In a recently started EU project called *RECALL – Augmented Human Memory* we aim to re-think and re-define the notion of memory augmentation. Therefore we are building tools for recording memories and enforcing them through technology.

---

\(^1\)http://www.fitbit.com/

\(^2\)http://www.endomondo.com/

---

**Memory Recording**

Recent developments in capture technology and information retrieval allow for continuous and automated recordings of many aspects of our everyday lives, both physically and mentally. We are currently creating concepts and building prototypes that attempt to harness these trends and develop a new paradigm for memory augmentation technologies that are technically feasible, desired by users, and beneficial to society.

**Explicit Recording**

Whenever we stop to capture the moment by taking a picture or video, we explicitly take a snapshot of that moment. Hence, explicit recording entails the conscious attempt to record a memory. Posting on Twitter, Facebook or Instagram would be considered a conscious effort to communicate a thought, experience or feeling. When users make the conscious decision to record a moment or content item, they should have an appropriate tool at hand to do so. We have been experimenting with different approaches concerning user dialogues that are user-triggered and walk the user through a sequence of tasks to be completed in order to record a moment. Therefore, we built an Android app that allows users to capture moments by displaying a wizard asking the user to perform a sequence of actions, such as taking a picture, recording an audio snippet, video or composing a note. The app artificially limits the available time for conducting each step to avoid lengthy interactions. We are currently working on enhancing the app to include the user’s momentary mood, song, place, surrounding people or feelings. The recorded memory is locally stored and can be retrieved later by searching or browsing. Additionally we are working on an automated quiz generator using these memories to attenuate memories and support long-term memory transitioning.
Further, we are looking at mnemonic techniques that are suited to be applied to a technologically supported application. The method of Loci, for example, is an efficient way to store data in the human long-term memory and is widely spread under memory competitors. It works by visually organizing information in imagined spaces of a mental environment - so-called memory palace -, which makes it easier to recall items and keep them in order. We are currently developing a prototype that aims at making the method a valuable everyday tool by reducing the effort of building a memory palace anew, hence bringing down the mental overhead. It works by allowing users to take pictures of their favorite locations (e.g., living room, garden) and fill these places with custom content, such as text, pictures, links, or documents. By extending the sharing capabilities of the browser, users can easily place items they come across online into one of their locations (Fig.1, 2). Again, we use a quiz format to prompt the user to recall contents from certain locations.

With explicit memory recording there is, however, a trade-off between enjoying a moment by being fully focused at it, and making the decision to record it by taking out a device and going through a designated sequence of steps. Between un-obtrusiveness and memorability there is a sweat spot, we believe, which we are aiming to find.

Implicit Recording
To make sure the focus of attention is where it is needed - the current moment, the currently read article - explicit tools for memory capture may not be the best solution as pointed out. The time required to take out the phone or camera, aim it at the object of interest and make that picture to retain that moment often times disrupts the enjoyment of it. Other times we only realize that a moment or detail was worth capturing when it has passed.

Therefore we are looking at implicit ways of logging data that can be automatically collected from the user or the environment. Aforementioned devices, such as Fitbit, allow a constant logging of movement data. We can further infer from smartphone and app usage who a person interacted with over the course of a day, what events went by recorded by the calendar, or which locations were visited during the day.

Additionally, services like Facebook, Foursquare or Twitter provide us with APIs to retrieve user activities. From this data we can construct a summary of distinct events a person experienced over the course of a day, week, month or year, thereby creating digital memories that can be indexed, searched, or browsed later on. Context awareness is highly beneficial as it allows us to infer what state a person is in or which application is currently pre-dominant on the user’s phone [5]. We are currently developing a modular technology platform that pulls information from all kinds of services and bundles them into a digital memory system.

Challenges of a Holistic Quantified Self
Combining implicit and explicit data capture to end up with a life logging solution that comprises both physical and mental states of people requires tackling a number of challenges.

Meaningful data
Meaningful data heavily relies on the data quality and the legitimacy of conclusions we draw from them. This is especially true for implicitly collected data, where inferential conclusions may be ambiguous.
Technology constraints
There are constraints on what we can track when it comes to physiological and psychological activities. Despite the progress made regarding tracking physical data, tracking mental activities is still suffering from numerous limitations: eye trackers are used to capture users’ attention focus and Electroencephalography (EEG) is used to record the electrical activity along the scalp. Unfortunately, these techniques only give us a partial picture. Additionally, we still have to accept the fact that certain values are simply not attainable in a non-invasive way with current technologies (i.e. blood sugar levels, kidney values).

User acceptance
We may design software as well as hardware in order to support human memory. In the end it is still up to the user and her willingness to actually use these technologies in order to decide whether they are feasible, effective, usable and fashionable. To reach user acceptance, these technologies will need to be unobtrusive, non-invasive and informative when it comes to the presentation of the data that they are logging.

Call to action
Simply collecting data and inferring activities may not be enough. The way this data is processed and presented is crucial. Data alone is useless until we derive some meaning from it and give the user actual information about her state, progress and possible goals. Intelligent algorithms come into play when it comes to making meaning of data and deriving concrete user recommendations on how to change behavior regarding health practices, fitness or environmentally sustainable choices.

Concluding, there is always room for discussion whether holistic logging is a good idea in general. The moment we leave it up to algorithms which moments we are actually going to remember, brings up a range of ethical questions. Which memories should be attenuated? which ones should better tried to be forgotten?; and is there forgetting in a system that nearly never runs out of memory space? These are the issues we are trying to explore through both technological prototypes and active discussions.

Acknowledgements: This work is funded by the DFG within the SimTech Cluster of Excellence (EXC 310/1) and by the EU within the Recall project (No. 612933).

References
Towards Mental Balance: A Quantified Self Approach for Communicating Mental State

Abstract
Today's world focuses on balance, balance of self and group, work and personal time. Mental balance is more than topical, "Did I spend enough time thinking about my proposal?" Cognitive experiences and mental state also play a role in mental balance. Elements of daily life like activity engagement and attention flux also make up mental balance. Personal attentional metrics have primarily relied on subjective evaluation, making it difficult to compare across other activity attention levels. New mobile and wireless Electroencephalographic (EEG) devices can unobtrusively collect objective user-specific task engagement in intra-activity. These new EEG devices provide on-board data collection, wireless communication, long-lasting battery life, and reduced setup time. By subjectively measuring and archiving user engagement (how focused the user was) as well as activity engagement (what the user was focused on) information, new engagement prosthetics can help facilitate review of user's personal values and identifying engagement trends.

Author Keywords
Engagement; Quantified Self; Mobile; Android; Electroencephalography (EEG); Biometrics

Robert Beaton
Virginia Tech
Department of Computer Science
Blacksburg, VA 24060 USA
rbeaton@cs.vt.edu

D. Scott McCrickard
Virginia Tech
Department of Computer Science
Blacksburg, VA 24060 USA
mccricks@cs.vt.edu
Engagement Metrics

Our initial personal engagement index uses a metric defined by Alexander Pope that derives values from EEG powers [9]. This metric is computed by obtaining EEG readings for Alpha, Beta, and Theta brainwaves and applying the following formula:

Engagement Index = \frac{\text{Beta}}{(\text{Alpha} + \text{Theta})}

This engagement index is represented by a decimal number between 0 and 1. The scale is notably unique for each person, such that if two people both have values of 0.7 for their engagement index, it does not necessarily mean that they are equally engaged. It should be noted that Pope’s metric was derived with a specific activity in mind and may not be scalable to other activities. We are investigating appropriate alternate metrics as well.

ACM Classification Keywords

Design; Experimentation; Human Factors; Measurement

Introduction

What do “mentally balanced” and “mental state” really mean? They can (and have) taken on many meanings, often stemming from an emotional or visceral understanding by technology of the users’ state. Indeed, Don Norman, in his Emotional Design book, separates the emotional aspects of design from the cognitive ones that he focused on earlier in his career [7]. Meyer describes wellness as composite of life elements consisting of mental state, feelings and social interactions [6].

There are currently limited ways for a user to objectively track their mental performance throughout their day [5]. Engagement is a particularly useful and actionable mental metric. It is also difficult for our minds to track naturally, as we typically only remember general information about how engaged we typically become when performing a particular activity. The lack of specific, accurate, engagement information about individual instances of common, daily activities is a problem worth addressing. New advancements in wireless EEG devices offer a way to objectively measure user engagement while storing the results for later review.

By creating biometric models of when users’ cognitive experiences, and by aggregating them in a way that is meaningful to the users, our approach enables users to make informed decisions about their choices for tasks moving forward. Much of the recent work in this area has proposed to automatically adjust aspects of an interface based on possible or perceived interruptors [4]. But this approach ignores the explicit desires of the user: perhaps the user is locked in on a task, or perhaps multiple tasks are all important and the user is willing to take performance (and mental health) degradation. Too often interfaces seek to do things for the user, e.g., to control when interruptions take place by limiting access to information.

Our work focuses on developing tools and use cases to address this. Personal engagement monitoring research acts as part of the growing Quantified Self movement. The idea of this movement is to give the everyday person the ability to log, analyze, and productively apply information about their body. Popular examples of devices that fit into this movement are the Jawbone up, FitBit, and Nike Fuelband. All of these devices are essentially unobtrusive pedometers and life loggers with exceptionally accessible user interfaces. They have allowed the everyday person to statistically analyze their activities, all without any amount of specialized knowledge. However, the trend we have noticed is that most of these devices focus primarily on the physical aspects of the user’s life [6].

Engagement & Arousal Monitoring

No two brains are the same, as such EEG derived engagement indices are useful for comparing activities by the same person, but not across people. To describe engagement activity, we can show the user a relative metric rather than an absolute number. We show the change of their current engagement index above or below their baseline index. This high, neutral, low conceptualization of engagement is similar to other papers in the field that visualize engagement and arousal [5].
Arousal is a supplemental metric to engagement in our research. In simple terms, changes in heart rate can indicate that the user has experienced some exciting event in their daily activities [8]. Engagement and emotion are regulated through a set of complex feedback loops between the brain and the cardiovascular system [8, 10]. Consequently, the inclusion of heart rate measures with Cardiovascular Nervous System indicators will likely provide a more holistic picture of the many cognitive and affective processes that are related to performance-relevant states such as stress.

**Why do we need tools like this?**
The objective of this work is to design tools that allow the user to reflect over their personal engagement levels throughout a day, week, or month. But data-logging isn’t enough [1, 2]. *What will the user do with this data? How will they interact and interpret it?* Initial design requirements are listed to the left.

We have conducted a workshop on biometric engagement design as well as a semester long prototyping project with 3 senior undergraduates to begin investigating these questions. We found that users wanted to know comparative engagement values, not necessarily based around time.

As an example, one of our prototypes focused on providing a categorical view of the engagement data. Our favorite design to support the categorical comparison scenario was what we called a "Bubble UI". An example of this concept can be seen in Figure 1. Users are presented with "bubbles" labeled with their activity (derived from calendar scraping). The size of the bubble correlates to their mean engagement score during the activity. Users can quickly determine which activities they were most and least focused in.

Numerical engagement and timestamp values were available by tapping a bubble for more information.

This work is part of a larger research project focused on helping people achieve temporal understanding of derived engagement through prototyping-toward knowledge that leads to improved wellbeing. Deriving engagement through a combination of unobtrusive objective (biosensed) as well as subjective (calendar scraping, social media scraping) methods addresses two of the dimensions traditionally associated with engagement: user level and activity type.

**Conclusion and Future Work**
The trend of wearable devices moving towards smaller, faster, and robustness gives us confidence in proceeding with cognitive biometric tracking [1,2]. Current EEG devices offer the reliability of 100+ sensor devices in less than 14, and provide the mobility to be worn in new and exciting scenarios.

In the quantified self research field, a large stable of work is focused on physical wellness. There has been less work developed towards mental wellness and cognitive tracking. To do that we are investigating ways to combine objective and subjective user engagement, activity engagement, and arousal volatility as a means to enable reflection.

As an exploratory tool, we have begun development on an initial multimodal-tracking set-up and user interface focused on reflecting on longitudinal engagement trends, presenting information in categorical spheres. This work is hardware independent by design, focusing

---

Engagement information displays should at minimum:

- **Quickly glancing at the application should give a user useful information about their overall engagement trends (based off of categorical organization).**

- **Contextual information, i.e. events on a user’s Google calendar, needs to be available in the application**

- **Real time as well as historic data about a user’s engagement should be easily accessible.**

Beyond Quantified Self: Data for Wellbeing 36 Workshop at CHI2014
on data presentation regardless of the devices used to collect it. This allows users to review and compare their engagement trends by time and activity.

Our ongoing work examines how biometric data can be combined with other readily available information about user activity to provide a contextually connected view of the user’s behavior. Our efforts at calendar scraping associates user events and deadlines with changes in biometric data. Geographical information from a mobile phone’s GPS provides a continuously updated view of user location, highlighting how changes in location correlate with changes in biometric data. Information from online classroom management tools like Sakai and Scholar augment these other data sources with course-related deadlines.

Future work needs to be done to investigate how objective engagement information can be used in practice, and which metrics are appropriate. Tools like the Fitbit and heart rate monitor tracking devices have seen steady adoption and continued use for longitudinal personal informatics review.

**Acknowledgements**

Thanks to Shuo Niu, Andrew Weckstein, Ivy Jeong, Michael Barnes, Jayanth Prathipati, and Ryan Merkel for their development and brainstorming support. Special thanks to the Virginia Tech TLOS program as well.

**References**


Inbodied5 and Future Ghosts: sense-making for QS Wellbeing Support

m.c. schraefel
ECS, U of Southampton
Southampton, UK
SO171BJ
mc+qs@ecs.soton.ac.uk

Abstract
We can collect shed loads of data about our physiological processes. So far applications have presented much of this data in unmediated or naïve ways to their users: a person walks 7 steps, they see 7 steps. This paper presents the inbodied5 as a model for re-presenting quantified self (QS) data for wellbeing; Future Ghosts proposes an application driven by this model for planning QS backed wellbeing practice.

Author Keywords
Wellbeing, quantified self, inbodied5, models

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

Introduction
As neuro-physical-electro-chemical-psycho-social creatures, we are incredibly complex systems. These systems are deeply interconnected: our nutrition affects our capacity to move; our movement affects our cognition [9]; our socialization affects our physical wellbeing [7]; our cognition affects our sleep. These are just a small set of the combinatorial interactions that represent us. And yet, despite this complexity of interactions, so far our research and commercial applications in this space have largely focused on representing sensor data in isolation and as rather simplistic counts. A health application with sensor and app may track steps (pedometer/accelerometer data) and movement in sleep (actigraphy); it may connect with a food logger to estimate calories spent (based often on self logging and not deeply accurate [1] databases of food calorie values), but the connections between these systems is missing. There may be a weak and dubious connection such as “you’ve burned 10 calories doing some steps therefore you can eat ten more calories today.” Or there may be no connection: a person wishes to loose weight, has a wifi scale, uses a sleep monitor, has a food logger, all

Beyond Quantified Self: Data for Wellbeing 38 Workshop at CHI2014
potentially from the same company device ecosystem. The data may show calories have dropped but weight is static. It also shows that sleep is disrupted. If the person doesn’t know that sleep has a key effect on weight loss, they may simply keep dropping calories, which can actually further stall weight loss.

It may be time, therefore, for us in the quantified self space, to look towards models that help us support a person’s sensemaking around wellbeing data. To this end, we propose two mechanisms: the inbodied5 model and Future Ghosts. Inbodied5 is a model for wellbeing though which we can associate and correlate wellbeing data analysis. Future Ghosts is a path for leveraging collective data around the inbodied5 for greater global wellbeing.

INBODIED 5: a model for wellbeing
We are complex systems. Indeed, in physiology the body (of which the brain is a part) is factored into 11 systems from skin and nerves to excrement and sex. These systems interact with each other. The inbodied5 is a model of 5 essential or fundamental processes among these systems that research shows we need to optimize or mortality risk increases significantly. Fundamentally, we need to move, think, eat, socialize and sleep. And we need learn and practice the skills for each to the degree that they have a positive effect.

To eat and sleep may seem obvious members of the 5: if we do not eat for a period of time, we starve and die. If we do not sleep for a period of time, we die. Our bodies also require movement. Sedentarism – the lack of movement – is being proposed as a new coronary risk factor [2]. Likewise, research shows unequivocally that mortality rates are higher for people who do not socialize with each other in the physical world [5][7]. Similarly, engaging with a subject deeply, such as learning a language, practicing explaining complex subjects, seems to have a protective effect against physiological processes like alzheimers [6].

We offer these five processes not necessarily as final, but as those where (1) current research shows undeniable associations with mortality and (2) that all of us do of necessity on a largely daily basis. While this model offers us a set of parameters against which to quantify factors of wellbeing, what is particularly critical in this model is the interactions it supports to optimize wellbeing. If we want to reduce our body fat, most of us look to some aspect of food. With the inbodied5 model, we can also look at performance on other captured values such as sleep and movement.

New Factors to Quantify: Social & Cognitive
With the inbodied5 we have the opportunity to consider how to capture two new factors for wellbeing: degree of social interaction; depth of cognitive engagement. It is beyond the scope of this paper to detail such measures, but there is scope to do so. For Cognitive Depth, we have concepts like Flow [8] being sufficiently challenged by a task to be engaged and not bored and to feel stimulated by it. There is also Deliberate Practice [4] the uncomfortable component of working at those concepts that we experience as difficult until we have made sense of them and can execute them. There is also work around brain games that is a specialist

---

1 One list of the 11 systems is here

2 Usually, sadly, only calories (rather than nutrient profiles or timings, but that’s another issue).
deliberate practice used to help keep people cognitively independent that may act as a measure from time to time the way one checks their current mile pace and heart rate when exploring strength improvements. For social measures, there may be a variety of qualities we can begin to sense, from simple counts of number and frequency of engagements with another during a day, to types of sentence utterances such as length of time listening vs speaking.

We already know that relationships and cognitive engagements have life and death effects on our wellbeing. By sensing attributes of these exchanges, we have the opportunity with the inbodied5 model to contribute new understanding both around what kinds of qualities in these interactions best support wellbeing, but also to look at how these practices are co-effected. We already know that a person with poor sleep quality performs less well cognitively. Does a person with poor sleep socialize more or less frequently/deeply? We also know that less frequent movement during the day, thus more sitting, has a negative effect on health that is not offset by say working out for an hour after sitting all day [Dunstan]. Is the same true of social interaction: that a lack of social engagement during the day, and its effects on sleep or eating, can be offset by a wild weekend?

The key take away of the inbodied5 model for quantified self’s attention to quantified wellbeing is that it gives us a fundamental way to begin to consider both the data we wish to capture and how we wish to represent it for wellbeing sensemaking.

**Future Ghosts: Being health ancestors**

A opportunity for gathering data around the inbodied5 is to help us potentially see our holistic health futures before we embark on a path. For instance, if we are interested in burning some fat, and we’ve struggled with this in the past, a collection of quantified self data from many participants rendered as future ghosts would let us find data aggregate stereotypes of people like ourselves me (perhaps in terms of age, gender, height, weight, activity level) who are several weeks or months out from us in terms of a practice of interest, like a diet. We may use the computational power over the data to map our own inbodied5 data to find those closest to us who have already achieved what we are striving to do, or who are simply further into the process than us. We can look for models of success, where success may be taking X pounds off and keeping them off over a year, and we can look for when and where we may expect setbacks. In particular, with the inbodied5 as a model we can see how things like sleep quality or movement or social engagement correlates with progress. Perhaps especially, we can see from the evidence of even the best exemplars that performance is cyclical rather than constant. In other words with just the data from the inbodied5 model, we can develop a more nuanced view of wellbeing that respects better the complexity of us, and the inter-relation of these fundamental 5 processes of life in a body.

**Future Work Ghosts**

A challenge for something like an inbodied5 Future Ghost is boot strapping: where do we get the data? While we have identified two new types of data for sensing – social and cognitive – companies are already capturing big chunks of the other three: food, movement and sleep. Makers of monitoring tools from...
apps like Runkeeper that track walking, running cycling data with the accelerometers and gps capacity in a phone to dedicated performance computers like Garmin’s Edge to services like Strava that provides a way to share and compete with others socially are already capturing tremendous amounts of data about us. There are now APIs like HealthGraph by Runkeeper.com3 that are letting these applications share data between each other. None of these services, however, are releasing this data in any kind of anonymised or aggregate form for research. In speaking with many of these companies, it’s clear most wish to support open data, but several have told us they’re small and do not have the resources to contribute development cycles for such pro bono work. It may be that the quantified self community could take as a Social if not Grand Challenge, working with these developers in this growing industry to make it easy to publish data; to work with individuals to make it easy share their data and know that it is safely anonymised. Offering tax incentives to businesses that create open-data exports of their data (against some standard of usability, so not aggregated into obscurity) may be one mechanism to nudge data release, and thus be seen as Good Companies for doing so. Open Data becomes a consumer decision point for engaging with one provider rather than another, for example.

Conclusion

With the inbodied5 we have a fundamental model to help us both contribute to knowledge about and improve understanding of our own wellbeing in a from a quantifiably richer way. We also have two new-ish areas to consider quantification for wellbeing. With Future Ghosts, we have an example of how that richness might be leveraged to help with wellbeing sense-making to help choose paths based on evidence of QS-backed success.

References


---

3 http://runkeeper.com/developer/healthgraph/
Organizers

**Jochen Meyer** is director of the R&D Division Health at the OFFIS Institute for Information Technology where he is responsible for numerous national and international research projects on pervasive health systems, ambient assisted living, e-health and others. He was co-organizer of workshops on pervasive health systems, was workshop chair of the PervasiveHealth’13 and is local chair of PervasiveHealth’14.
Contact: meyer@offis.de

**Steven Simske** is an HP Fellow in the Printing and Content Delivery Lab (PCDL) in Hewlett-Packard Labs, and is the Director and Chief Technologist for the HP Labs Secure Document Ecosystem program. He has advanced degrees in Biomedical and Electrical Engineering, along with a PostDoc in Aerospace Engineering. He is a member of the World Economic Forum’s Global Agenda Council on Illicit Trade and an IS&T Fellow.
Contact: steven.simske@hp.com

**Katie Siek** is an associate professor in Computer Science at the Indiana University Bloomington. She researches how socio-technical interventions affect personal health and well-being. Her research is supported by the National Institutes of Health, the Robert Wood Johnson Foundation, and the National Science Foundation including a five-year NSF CAREER award. She has been awarded a CRA-W Borg Early Career Award and a Scottish Informatics and Computer Science Alliance Distinguished Visiting Fellowship.
Contact: ksiiek@indiana.edu

**Cathal Gurrin** is a lecturer at the School of Computing, at Dublin City University and a faculty member of the Centre for Digital Video Processing and the Human Media Archives group at Dublin City University. Research interests cover Human Digital Memories, the indexing and content-based retrieval of information in all media, text, image, audio and especially digital video.
Contact: cgurrin@computing.dcu.ie

**Hermie Hermens** is Director for Telemedicine at Roessingh Research & Development. He is Professor for Telemedicine at the University of Twente, at the Research Institutes Mira and CTIT, visiting Professor at Glasgow Caledonian University, Editor in Chief J. Back and Musculoskeletal Rehabilitation, and Fellow Int. Society Electrophysiology & Kinesiology.
Contact: h.hermens@rrd.nl