What's Happening in the "Quantified Self" Movement?

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Abstract: Rapid adoption of wearable tracking devices and motion sensitive apps has led to the development of the "Quantified Self" movement (QS). Some in the learning sciences community have begun to take notice and incorporate ideas from QS into the research and design of new learning environments. Yet the QS movement is still new enough that very little is known about it, and there are many open questions about how QS might be of value to the learning sciences. This paper provides some history of the movement and through a qualitative analysis of a public video corpus of QS presentations, identifies the variety of participants, the reported motivations driving individuals to self-quantify, and the data analysis activities of some individuals active in the movement. Opportunities for future research and design efforts in the learning sciences are also discussed.

Introduction

The reduced cost and increased availability of wearable devices and tracking apps has led to the development of what the popular press has called the "Quantified Self" (QS) movement. QS centrally involves extended tracking and analysis of personally relevant data. Given the emphasis on data and new technologies, QS is now starting to be discussed with research associated with the learning sciences. For example, QS tools and techniques appear in new frameworks for supporting learners in their own reflections on their learning processes (e.g., Rivera-Pelay, Zacarias, Müller & Brown, 2012), as a personal and consequential data source for input into educational games (Ching & Junicke, 2013) and in new designs for learning activities that turn everyday school experiences, such as recess or a walk to the library, into objects for students to study (e.g., Lee & Thomas, 2011; Lee & Drake, 2013).

These are all new developments. If QS is to continue to grow and overlap with work in the learning sciences, there is a fundamental question that should be asked of a movement that is still so new. Namely: What is happening in the Quantified Self movement? More specifically, who is involved in QS, what leads to them being involved, and what are some of the specific data collection and analysis activities undertaken by these "Quantified Selfers" (QSers)? Secondarily, what should the LS community seek to gain from understanding the QS movement? One goal of this paper is to identify a few features of the QS movement that we may wish to examine, leverage, or modify so that we can better understand and design for technology-supported learning that involves people having frequent encounters with data.

A Brief Background on QS: Origins, Growth, and Interactions

While there have been longstanding efforts to develop and promote wearable technologies, the past decade has seen a more aggressive effort among businesses to produce and distribute consumer-level wearables that emphasized physical activity tracking (Lee & DuMont, 2010). For example, in 2006, Apple announced an activity sensor and iPod kit that ultimately led to the Nike+iPod system. This incorporated a sensor embedded in the sole of a running shoe that could communicate wirelessly with an iPod. Around the same time (2007, to be exact), Kevin Kelley and Gary Wolf, two editors with *Wired* magazine who were credited with coining the name "quantified self", were meeting informally with a number of entrepreneurs and technology enthusiasts in California's Silicon Valley. Kelley and Wolf proceeded to report on new technologies and opportunities being explored through major periodicals (e.g., *The New York Times*) and presentations (e.g., TED Talks). As word about QS spread, informal local QS interest groups comprised of technology enthusiasts, hobbyists, and others interested in personal data began to coordinate face-to-face, regionally-based "meetups".

Rapidly growing popular interest in self-quantification led to the formation of a support organization, Quantified Self Labs (QS Labs). QS Labs launched a website (quantifiedself.com) with online guides and recommendations for how people in even remote locations could start their own QS meetup group. QS Labs also established an online discussion forum with over 2300 registered accounts, as of late 2013. The number of QS meetup group members expanded rapidly from one California-based group to 96 groups distributed across six continents. In early 2013, membership in QS meetup groups was already over 10,000 (Lee, 2013).

Face-to-face meetups typically occur every 1-2 months and feature volunteers giving ten-minute "Show & Tell" (S&T) talks, followed by a brief interactive discussion. These talks usually feature reporting of a personal self-data project followed by a personal reflection on what the presenter learned as a result. A number of these S&Ts are voluntarily recorded and uploaded to an online video repository, where they are then curated by QS Labs and posted publicly on the main quantifiedself.com page. In 2011, an international conference series was established. In its upcoming sixth iteration, the conference features keynote addresses related self-quantification, volunteers presenting refined versions of their regional S&Ts, and informal "breakout" sessions for QSers to meet together in a separate room to discuss common interests and help push the QS movement further.

Theoretical Perspectives

While QS can be understood from a number of theoretical perspectives. I opted to view participation in QS as an instance of participation in an affinity space (Gee, 2005). An affinity space refers to a social affiliation organized around a common endeavor that involves variable degrees of discretionary participation and highly distributed, multidirectional exchanges of knowledge across various media. The canonical example of an affinity space is the social affiliation associated with a video game. Video games do not exist in isolation but rather are part of a set of practices that involve knowing and doing in particular ways with particular tools. As such, a number of ways exist for one to become an active participant in the affinity space associated with a video game that go beyond strictly playing the game. This can include posting in message boards, reading published strategy guides, or even getting verbal referrals and recommendations related to the game from knowledgeable peers. These pathways are designated as *portals*. In the case of QS, the quantifiedself.com website, the discussion forums, the meetup groups, public news media, and the new tracking devices and apps that one can purchase are all portals into QS.

Also important to the maintenance of an affinity space are *generators*. Generators are the entities that produce content and representations against which participants create meanings. In a video game affinity space, the game itself is a generator, as it has embedded in it many signs and representations that participants interpret and act upon. Portals can also be generators as well, as would be the case with a message board about a video game that mediates participants' understandings of what representations are meaningful in the game while also serving to generate new representations itself. Within QS, the S&T talks and the international conference are generators, as are discussion boards, and various other tools created and shared by QSers for producing novel data representations.

Self-quantification can take the form of a highly tailored set of data practices that build upon (and are also constrained by) the specifics associated with one's lives and circumstances (Azevedo, 2011). The canonical QS device may be something like a FitBit activity tracker or Zeo sleep monitor and involve tracking activity or sleep in the interest of improving health, but QSers also engage with self-data that collected in a range of ways from diverse activities. One goal of this paper is to illustrate some of that diversity.

Research Approach, Data Sources, and Analysis Process

In an ongoing effort to understand some of activities and participants in the QS affinity space, I have been engaged in roughly a year's worth of participant observation. This included interacting with QSers in a number of capacities, including attending meetups in my region, speaking on the phone or in person with personnel at QS Labs about their backgrounds and their current activities, attending the annual conference and talking with attendees and presenters, participating in QS discussion boards, and purchasing and using self tracking devices to examine data about my own activities. From these activities, I have obtained a number of artifacts for analysis, such as conference programs, field notes, message board exchanges, and transcriptions. For the current paper, I am drawing primarily the user-contributed online videos of S&R presentations (N = 220 and spanning from 10/2008-09/2013). This particular data source has inherent limitations and biases associated with how the videos were captured and which ones were ultimately selected for public dissemination (Hall, 2000). Still, it served as a useful and public source for understanding who participates in QS and what activities QSers pursue.

Demographic information such as gender, approximate age range, and ethnicity were identified based on appraisal of immediate information such as short video snippets, names of the participants, and comments posted with all the videos. A subset of 12 videos (a little over 5% of the entire set of videos) representing a range of topics and self-data projects was selected for transcription and further analysis. The transcripts of these videos were coded iteratively. The first round of codes served to flag all statements in the presentations that involved descriptions or motivators driving the collection or analysis of data. These codes were then refined by cross-case comparisons and through code frequency analysis. The videos were then re-reviewed and then re-coded. Following that step, codes were organized into major categories induced from this second review and analysis of the coding scheme. This process yielded a set of common features associated with the use of self-data and a set of specific examples to share, presented below.

Findings from Show and Tell Video Analysis

The age of the presenters appeared to be normally distributed, based on visual appraisal. There were clear majorities for specific genders and ethnicities. With respect to age, there were estimated to be 58 presenters (26.9%) in their mid-20s to mid-30s, 93 (43.1%) in their mid-30s to mid-40s, 49 (22.7%) in their mid-40s to mid-50s, 16 (7.4%) in their mid-50s to mid-60s, and 4 who were unclassified. For gender, there were 174 (82.5%) male presenters, 37 (17.5%) female presenters, and 9 joint presentations that had a male and female.

For ethnicity, there were 185 presenters (84.1%) who were categorized as White or of European descent, 24 (10.9%) Asian, 6 (2.8%) Hispanic or Latino, and 5 (2.2%) who were unidentified.

Through the coding process described above, I settled upon a coding scheme with 50 codes, from which 7 categories emerged. For this paper, I discuss three of those categories: *Motivations* for pursuing self-quantification, *Enabling conditions* that could build on initial motivation and supported the presenter's ability to pursue self-quantification and *Analyses of self-data* that had been collected.

Motivations

The primary identified *motivations* among the analyzed presentations included ties to ongoing personal interests (9 out of 12), a need articulated in part by a family member (3 out of 12), a concern for personal health (5 out of 12) and, a professional or commercial interest (3 out of 12). In addition, there were ways in which being a participant or attendee at QS gatherings helped to provide inspiration for doing some self-quantification. To illustrate, consider how Rajiv described at the beginning of his Show & Tell presentation (entitled "Papa, what should I read?") what led to his quantification of reading:

> Rajiv: Ok so I love to read, I've read all my life…I have all these memories of leaving the library with armloads of books…A few years ago I started tracking my books, not for a project, but simply because I couldn't remember. My little girl is growing up and interested in reading my books, not just hers. She always asks me, "what can I read?" and I couldn't remember the name of the title or the author. So I started a simple spreadsheet of the name, the author, when I started, when I finished it, I gave it a star rating based on how much I liked it…A few years ago at a QS [meetup] a person gave a presentation on an information diet. It struck me, maybe there is something worth understanding from my tracking of books.

There are several features to note from this short excerpt. One is that Rajiv characterized reading as a lifelong pursuit tracing back to his youth, which suggests that while the quantification of reading was a relatively new endeavor, it was also built upon a longstanding preference (Azevedo, 2011) he had maintained throughout his life. His reading was done for his enjoyment but was not something he formally quantified until his daughter asked for recommendations on what to read, and he discovered that he could not recall what books he had read. That ultimately led him to produce a spreadsheet to keep track of what he had read and when. Later in his presentation, Rajiv discussed that he had kept these records for four years. He then saw another self-quantification project at a meetup, and was intrigued enough to see if he could find out anything new from his own records of his reading. This appropriation of how others work with self-data into his own project is an instance of knowledge being distributed and appropriated by individuals (Gee, 2005). Taken together, the convergence of personal interest, a need stated by a family member, and a model from a more experienced QSer all jointly supported the pursuit of his self-quantification project to examine his own reading patterns.

As a second example of convergence, consider how Jules explained his motivation to analyze snoring.

> Jules: I am a snorer. This didn't really bother me because after all I couldn't hear my snoring. The same wasn't true for my wife who would let me know by means of an elbow in my ribs…So I went and took my phone and thought surely there is an app for that and looked and there were a few snoring apps, but there was nothing [good]… Hence, as I was looking at all these not very good apps, I could envision something much better which might be able to quantify things…to track your snoring through time and then be able to test if certain things affected your snoring…I've had loads of bad business ideas, and I thought, "hold on, maybe this is actually a good one!"…So I went to my wife and I said "Darling, darling I've got an amazing idea. You know all that money we've got saved up for a house deposit, why don't we employ a developer to build an app to measure snoring!"

In this example, Jules was both responding to a need to respond to the concerns of a family member (his wife, who was being awoken), and he also had hopes for developing a new app for a mobile phone as a business idea. In fact, one of the things Jules was doing through his S&T was advertising the app he had developed, "SnoreLab", while also describing his experiences with different snoring aids and how they affected his snoring. Also, as suggested by his past of having 'loads of bad business ideas' the decision to develop this app also seemed to flow from an ongoing preference for entrepreneurial pursuits. The convergence of this entrepreneurial streak along with an immediate need to deal with a snoring problem both help to explain what led to his engagement with the QS affinity space and why it took the form that it did.

Examples like those of Rajiv and Jules suggest that the motivations behind pursuing a self-data project are multi-faceted. It is not simply that someone abruptly decides to track some aspect of their life. Rather there can be several influences from many different spheres of one's life that leads to self-quantification. Among

QSers, it is well known that many people new to the space will excitedly initially try a tracking app or device for a few days but then cease using it. The exact reasons for this discontinuation has not been discussed heavily, but the experiences of those individuals who have gone beyond initial excitement with a tool and pursued a self-data tracking project suggest that motivation for self-quantification relies on the convergence of multiple personal and social forces, rather than general capabilities built into a tracking tool.

Enabling Conditions

QS participation is enabled by meetup groups and other physical and virtual *QS knowledge exchanges* (mentioned by 6 of 12), as well as the increased commercial availability of mobile and wearable technologies. The *ease of use* of a given tool or device or the *automatic data transfer* of data to another service were cited as being important for enabling self analysis (4 and 2 out of 12, respectively). Also of note was that half of the presenters highlighted how important *seamless integration* of data collection into daily activities was to their projects. While *ease of use* and *automatic data transfer* both helped in this regard, the high degree of integration was not an inherent feature of any given technology. Rather, *seamless integration* built upon *ease of use* or *automatic data transfer* along with some very small modification to existing routines. For example, in Matthew's comments during his presentation on how he lost 50 pounds by self-tracking illustrated how important he perceived that small modification could be:

> Matthew: I picked up a Wi-Fi Withings scale and started stepping on it everyday. Everyday, before even saying "hi" to my wife in the morning, I just stepped on the scale… This [accompanying app data display] is a screen that I interact with a lot every day. Obviously the scale feeds into the weight…I can't say enough about the scale. It is the beginning of my day.

While Matthew ultimately tracked a number of other things, such as some of his exercise and caloric intake, the scale and his ritualized use of it was key. The perceived prominence of ritualization appeared in how he titled his entire presentation (i.e., "One small step on a scale"), and also when he explicitly stated at the end of his presentation how important it was for him to take that initial 'step' and look at that data as a form of feedback so that he could successfully lose that amount of weight. The way in which tracking technologies are typically promoted is in a way that suggests the user needs to do little to nothing to obtain their data. Ultimately, experiences like Matthew's helps show that QSers are interested and willing to do just a little bit of extra work to obtain data about their activities, but it the amount of work really has to be very little. It appears from this and related cases that for QS activities to take hold, the data collection technology needs to fit easily into existing routines of everyday life rather than demanding some routine in life adapts to fit with the technology.

Analyses of Self Data

While there was one individual who used a moderately advanced statistical technique (i.e., performing linear regressions), the approach to analysis as shown in the presentations most often involved *identifying changes over time* (7 out of 12), *finding central tendencies* (6 out of 12), and *comparing across conditions* (5 out of 12). Change over time was an important feature for presenters like Matthew who had a goal in mind and needed to see how well they progressed on their goal. This often tied into *finding central tendencies,* although central tendencies could also operate outside of an immediate goal related to the modification of some behavior. For example, Robby was interested in seeing how much time and money he spent on various forms of transportation. He logged a month of his transportation using his mobile phone with some hacks he developed and then determined average speeds and costs to facilitate *comparing across conditions* (including walking, car rental, bus, driving his own vehicale, taxi, and Zipcar car sharing).

In discussing his results, Robby had some suspicions confirmed, such as the relatively high average cost of a taxicab and also that cabs tended to be the fastest mode of transportation. However, he was surprised by how much it cost to use Zipcar and how slow it was, especially relative to other means of automotive transit he had used. To explain this, he proceeded to verbally reconstruct the situation that generated the data:

> Robby: The least represented thing is the Zipcar…because it makes it look horrible with this data. I rented a Zipcar right when they had Hemp Fest downtown, so traffic was just awful and I got stuck in it. I was just trying to get away from it, and I ended up sitting in traffic for like 30 minutes and…I just took it back so I have a whole bunch of travel time that I was paying for. If you just look at Zipcar's rates by the time you are traveling it looks terrible.

Engaging in this kind of *data reconstruction* when looking at a data representation appeared in half of the presentations. This may ultimately speak to one of the unique and attractive features of participation in the QS affinity space: there is an inherently intimate relationship with the data that are collected because they are about 'the self'. As such, the ability to look at some of the resulting representations, tendencies, or changes over time leverages familiarity. The patterns or trends that are identified are not always taken immediately at face value. Rather, they are subject to additional scrutiny because the history of the data are known and the meanings of the data can also be consequential for how people live their lives because the data already come from their lives.

Parting Thoughts: What might LS Take from a Snapshot of QS?

The work in this short report is preliminary, but as learning scientists work on issues of practice, design, participation, and learning, there are some aspects of the QS movement in its current form that could stir future research interest and pose new research questions of consequence to LS. These include:

- *QS models how technical and social infrastructure can leverage personal knowledge and interest related to the self to motivate learning*. Among the things that LS can uncover through study of QS practices and participation is how the emergent combination of infrastructure, physical and virtual knowledge support, and space for individuals to customize and share their knowledge pursuits all work together to mobilize intimate knowledge and curiosity about the self in service of learning. What combinations of support, technical infrastructure, and know-how are necessary for QS to work?
- *QSers encounter disciplinary content and participate in versions of valued disciplinary practices.* QS represents a unique, emerging hobby in which QSers identify trends over time, look for central tendencies, and compare differences across conditions. They touch upon mathematical, statistical, and scientific ideas such as variability, correlation, and experimental design. What is the nature of QSers understanding of this content? Is QS an effective model for how learners in other settings could meaningfully participate in scientific and mathematical inquiry practices?
- *QS currently lacks heterogeneity in its participants.* The bulk of the QS participants appear to be middle-aged white males of European descent. While LS is often recognized for its work in areas of design, cognition, and modeling of learning, issues of equity still figure prominently in the field. If QS is a promising model for designing learning experiences, could the model work with different focal populations (e.g., young women from underrepresented ethnic groups)? If not, what supports would be needed to enable equitable participation? Are the gains from doing self-quantification with populations different from that most commonly associated worth the investment?

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