REVIEW

THE QUANTIFIED SELF:

Fundamental Disruption in Big Data Science and Biological Discovery

Melanie Swan

MS Futures Group, Palo Alto, California

Abstract

A key contemporary trend emerging in big data science is the quantified self (QS)–individuals engaged in the self-tracking of any kind of biological, physical, behavioral, or environmental information as n = 1 individuals or in groups. There are opportunities for big data scientists to develop new models to support QS data collection, integration, and analysis, and also to lead in defining open-access database resources and privacy standards for how personal data is used. Next-generation QS applications could include tools for rendering QS data meaningful in behavior change, establishing baselines and variability in objective metrics, applying new kinds of pattern recognition techniques, and aggregating multiple self-tracking data streams from wearable electronics, biosensors, mobile phones, genomic data, and cloud-based services. The long-term vision of QS activity is that of a systemic monitoring approach where an individual's continuous personal information climate provides real-time performance optimization suggestions. There are some potential limitations related to QS activity—barriers to widespread adoption and a critique regarding scientific soundness—but these may be overcome. One interesting aspect of QS activity is that it is fundamentally a quantitative and qualitative phenomenon since it includes both the collection of objective metrics data and the subjective experience of the impact of these data. Some of this dynamic is being explored as the quantified self is becoming the qualified self in two new ways: by applying QS methods to the tracking of qualitative phenomena such as mood, and by understanding that QS data collection is just the first step in creating qualitative feedback loops for behavior change. In the long-term future, the quantified self may become additionally transformed into the extended exoself as data quantification and self-tracking enable the development of new sense capabilities that are not possible with ordinary senses. The individual body becomes a more knowable, calculable, and administrable object through QS activity, and individuals have an increasingly intimate relationship with data as it mediates the experience of reality.

Introduction

What is the quantified self?

The quantified self (QS) is any individual engaged in the self-tracking of any kind of biological, physical, behavioral, or environmental information. There is a proactive stance toward obtaining information and acting on it. A variety of areas may be tracked and analyzed, for example, weight, energy level, mood, time usage, sleep quality, health, cognitive performance, athletics, and learning strategies (Table 1).[1] Health is an important but not exclusive focus, where objectives may range from general tracking to pathology resolution to physical and mental performance enhancement. In some sense everyone is already a self-tracker since many individuals measure something about themselves or have things measured about them regularly, and also because humans have innate curiosity, tinkering, and problem-solving capabilities. One of the earliest recorded examples of quantified self-tracking is that of Sanctorius of Padua, who studied energy expenditure in living systems by tracking his weight versus food intake and elimination for 30 years in the 16th century.[2] Likewise there is a philosophical precedent for the quantified self as intellectuals

Table 1. Quantified Self Tracking Categories and Variables

Physical activities: miles, steps, calories, repetitions, sets, METs (metabolic equivalents)
Diet: calories consumed, carbs, fat, protein, specific ingredients, glycemic index, satiety, portions, supplement doses, tastiness, cost, location
Psychological states and traits: mood, happiness, irritation, emotions, anxiety, self-esteem, depression, confidence
Mental and cognitive states and traits: IQ, alertness, focus, selective/sustained/divided attention, reaction, memory, verbal fluency, patience, creativity, reasoning, psychomotor vigilance
Environmental variables: location, architecture, weather, noise, pollution, clutter, light, season
Situational variables: context, situation, gratification of situation, time of day, day of week
Social variables: influence, trust, charisma, karma, current role/status in the group or social network

Source: K. Augemberg.[1] (Reproduced with permission from K. Augemberg)

ranging from the Epicureans to Heidegger and Foucault have been concerned with the "care of the self." The terms "quantified self" and "self-tracker" are labels, contemporary formalizations belonging to the general progression in human history of using measurement, science, and technology to bring order, understanding, manipulation, and control to the natural world, including the human body. While the concept of the quantified self may have begun in $n=1$ self-tracking at the individual level, the term is quickly being extended to include other permutations like "group data"—the idea of aggregated data from multiple quantified selves as self-trackers share and work collaboratively with their data.

The Quantified Self in More Detail

The quantified self is starting to be a mainstream phenomenon as 60% of U.S. adults are currently tracking their weight, diet, or exercise routine, and 33% are monitoring other factors such as blood sugar, blood pressure, headaches, or sleep patterns.[3,4] Further, 27% of U.S. Internet users track health data online,[5] 9% have signed up for text message health alerts,[6] and there are 40,000 smartphone health applications available.[7] Diverse publications such as the BBC,[8] Forbes,[9] and Vanity Fair[10] have covered the quantified self movement, and it was a key theme at CES 2013, a global consumer electronics trade show.[11] Commentators at a typical industry conference in 2012, Health 2.0, noted that more than 500 companies were making or developing self-management tools, up 35% from the beginning of the year, and that venture financing in the commensurate period had risen 20%.[12] At the center of the quantified self movement is, appropriately, the Quantified Self community, which in October 2012 comprised 70 worldwide meetup groups with 5,000 participants having attended 120 events since the community formed in 2008 (event videos are available online at http://quantifiedself.com/). At the "show-and-tell" meetings, self-trackers come together in an environment of trust, sharing, and reciprocity to discuss projects, tools, techniques, and experiences. There is a standard format in which projects are presented in a simplified version of the scientific method, answering three questions: "What did you do?" "How did you do it?" and "What did you learn?" The group's third conference was held at Stanford University in September 2012 with over 400 attendees. Other community groups address related issues, for example Habit Design (www.habitdesign.org), a U.S.-based national cooperative for sharing best practices in developing sustainable daily habits via behavior-change psychology and other mechanisms.

Exemplar quantified self projects

A variety of quantified self-tracking projects have been conducted, and a few have been selected and described here to give an overall sense of the diverse activity. One example is design student Lauren Manning's year of food visualization (Fig. 1), where every type of food consumed was tracked over a one-year period and visualized in different infographic formats.[13] Another project is Tim McCormick's Information Diet, an investigation of media consumption and reading practices in which he developed a mechanism for quantifying the value of different information inputs (e.g., Twitter feeds, online news sites, blogs) to derive a prioritized information stream for personal consumption.[14] A third example is Rosane Oliveira's multiyear investigation into diabetes and heart disease risk, using her identical twin sister as a control, and testing vegan dietary shifts and metabolism markers such as insulin and glucose.[15]

A fourth project nicely incorporating various elements of quantified self-tracking, hardware hacking, quality-of-life improvements, and serendipity is Nancy Dougherty's smile-triggered electromyogram (EMG) muscle sensor with an light emitting diode (LED) headband display. The project is

FIG. 1. One year of food consumption visualization by Lauren Manning.

designed to create unexpected moments of joy in human interaction.[16] A fifth project of ongoing investigation has been Robin Barooah's personalized analysis of coffee consumption, productivity, and meditation, with a finding that concentration increased with the cessation of coffee drinking.[17] Finally is Amy Robinson's idea-tracking process in which she e-mails ideas and inspirations to herself and later visualizes them in Gephi (an open-source graphing tool).[18] These projects demonstrate the range of topics, depth of problem solving, and variety of methodologies characteristic of QS projects. An additional indication of the tenor and context of QS experimentation can be seen in exemplar comments from the community's 2012 conference (Table 2).

Tools for self-tracking and self-experimentation

The range of tools used for QS tracking and experimentation extends from the pen and paper of manual tracking to spreadsheets, mobile applications, and specialized devices. Standard contemporary QS devices include Fitbit pedometers, myZeo sleep trackers, and Nike+ and Jawbone UP fitness trackers. The Quantified Self web site listed over 500 tools as of October 2012 (http://quantifiedself.com/guide/), mostly concerning exercise, weight, health, and goal achievement. Unified tracking for multiple activities is available in mobile applications such as Track and Share (www.trackandshareapps.com) and Daily Tracker (www.thedailytracker.com/).[19] Many QS solutions pair the device with a web interface for data aggregation, infographic display, and personal recommendations and action plans. At present, the vast majority of QS tools do not collect data automatically and require manual user data input. A recent emergence in the community is tools created explicitly for the rapid design and conduct of QS experiments, including PACO, the Personal Analytics Companion (https://quantifiedself.appspot.com/), and studycure (http://studycure.com/).

Table 2. Quotable Quotes from the 2012 Quantified Self Conference

- Can I query my shirt, or am I limited to consuming the querying that comes packaged in my shirt?
- Our mission as quantified selves is to discover our mission.
- Data is the new oil.
- The lean hardware movement becomes the lean heartware movement.
- Information wants to be linked.
- We think more about our cats/dogs than we do our real pets, our microbiome.
- Information conveyance, not data visualization.
- Quantified emotion and data sensation through haptics.
- Display of numerical data and graphs are the interface.
- Quantifying is the intermediary step…exosenses (haptics, wearable electronic senses) is really what we want.
- Perpetual data explosion.
- The application of the metric distorts the data and the experience.

Motivations for quantified self experimentation

Self-experimenters may have a wide range of motivations. There is at least one study investigating self-tracking projects, the DIYgenomics Knowledge Generation through Self-Experimentation Study (http://genomera.com/studies/knowledge-generation-through-self-experimentation). The study has found that the main reason individuals conducted QS projects was to resolve or optimize a specific lifestyle issue such as sleep quality.[20] Another key finding was that QS experimenters often iterated through many different solutions, and kinds of solutions, before finding a final resolution point. Some specific findings were that poor sleep quality was the biggest factor that attributed to work productivity for multiple individuals. For one individual, raising the bed mattress solved the problem, and for another, tracking and reducing caffeine consumption. Another finding was that there was not much introspection as to experimental results and their meaning but rather a pragmatic attitude toward having had a problem that needed solving. A significant benefit of self-experimentation projects is that the velocity of question asking and experiment iterating can be much greater than with traditional methods. At the meta-level, it is important to study the impact of the practice of self-tracking. One reason is that health information is itself an intervention.[21] Some studies have found that there may be detrimental effects,[22] while others have documented the overall benefits of self-tracking to health and wellness outcomes as well as the psychology of empowerment and responsibility taking.[23–25]

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How the Quantified Self is Becoming an Interesting Challenge for Big Data Science

Quantified self projects are becoming an interesting data management and manipulation challenge for big data science in the areas of data collection, integration, and analysis. While quantified self data streams may not seem to conform to the traditional concept and definition of big data—"data sets too large and complex to process with on-hand database management tools" (http://en.wikipedia.org/wiki/Big_data)—or connote examples like Walmart's 1 million transactions per hour being transmitted to databases that are 2.5 petabytes in size (http://wikibon.org/blog/big-data-statistics/), the quantified self, and health and biology more generally, are becoming full-fledged big data problems in many ways. First, individuals may not have the tools available on local computing resources to store, query, and manipulate QS data sets. Second, QS data sets are growing in size. Early QS projects may have consisted of manageable data sets of manually-tracked data (i.e., "small data"). This is no longer the case as much larger QS data sets are being generated. For example, heart rate monitors, important for predictive cardiac risk monitoring, take samples on the order of 250 times per second, which generates 9 gigabytes of data per person per month. Appropriate compression algorithms and a translation of the raw data into aggregated data that would be more appropriate for long-term storage have not yet been developed.

Another example is personal genomic data from "SNP chip" (i.e., single nucleotide polymorphism) companies like 23andMe, Navigenics, and deCODEme. These files constitute 1–2% of the human genome and typically have 1–1.2 million records, which are unwieldy to load and query (especially when comparing multiple files) without specific data-management tools. Whole human genome files are much larger than SNP files. Vendors Illumina and Knome ship multi-terabyte-sized files to the consumer in a virtually unusable format on a standalone computer or zip drive. In the short-term, standard cloud-based services for QS data storage, sharing, and manipulation would be extremely useful. In the long-term, big data solutions are needed to implement the vision of a systemic and continuous approach to automated, unobtrusive data collection from multiple sources that is processed into a stream of behavioral insights and interventions. Making progress in the critical contemporary challenge of preventive medicine–recognizing early warning signs and eliminating conditions during the 80% of their preclinical lifecycle—may likely require regular collection on the order of a billion data points per person.[26] Specific big data science opportunities in data collection, integration, and analysis are discussed below in the sections data collection, data integration, data analysis, and opportunities in working with large data corpora.

Data collection: big health data streams

There is a need for big data scientists to facilitate the identification, collection, and storage of data streams related to QS activity. Both traditional institutional health professionals and QS individuals are starting to find themselves in a whole new era of massively expanded data and have the attendant challenge of employing these new data streams toward pathology resolution and wellness outcomes. Big health data streams can be grouped into three categories: traditional medical data (personal and family health history, medication history, lab reports, etc.), "omics" data (genomics, microbiomics, proteomics, metabolomics, etc.), and quantified-self tracking data (Fig. 2).[27] A key shift is that due to the plummeting cost of sequencing and Internet-based data storage, many of these data streams are now available directly to consumers. In the omics category of health data streams, as of January 2013 genomic profiling was available for $99 from 23andMe (sequencing 1 million of the most-researched SNPs) and microbiomic profiling was available for $79 from uBiome (www.indiegogo.com/ubiome) and $99 from the American Gut Project (www.indiegogo.com/americangut). A broad consumer application of integrated omics data streams is not yet available, as institutional projects[28,29] are themselves in early stages, but could quickly emerge from academia through consumer proteomics services such as Talking20 (the body's 20 amino acids) who offers $5 home blood-test cards for a multi-item panel (e.g., vitamins, steroids, and cholesterol).[30]

Data integration

A key challenge in QS projects and the realization of preventive medicine more generally is integrating big health data streams, especially blending genomic and environmental data. As U.S. National Institutes of Health director Francis Collins remarked in 2010, "Genetics loads the gun and environment pulls the trigger."[31] It is a general heuristic for common disease conditions like cancer and heart disease that genetics have a one-third contribution to outcome and environment two-thirds.[32] There are some notable examples of QS projects involving the integration of multiple big health data streams. Self trackers typically obtain underlying genomic and microbiomic profiling and review this information together with blood tests and proteomic tests to determine baseline levels and variability for a diversity of markers and then experiment with different interventions for optimized health and pathology reduction. Some examples of these kinds of QS data integration projects include DIYgenomics studies,[33] Leroy Hood's 4P medicine (predictive,

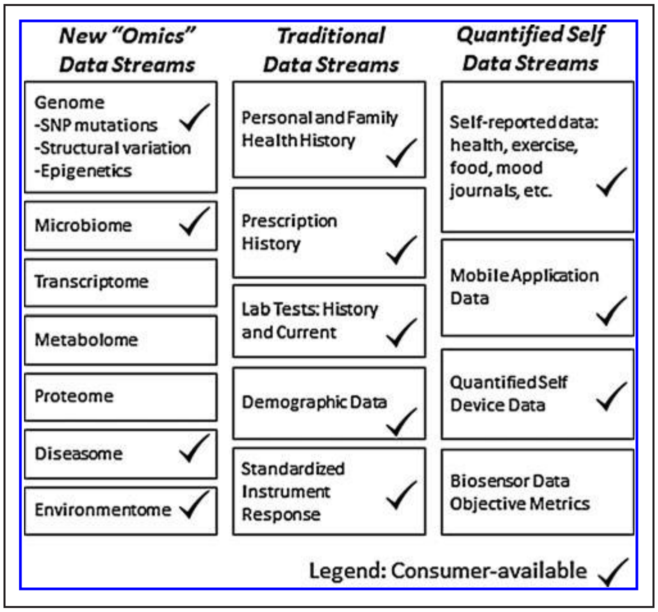

FIG. 2. Big health data streams are becoming increasingly consumer-available.

personalized, preventive, and participatory),[26] David Duncan's Experimental Man project,[34] Larry Smarr's Crohn's disease tracking microbiomic sequencing and lactoferrin analysis project,[35] and Steven Fowkes's Thyroid Hormone Testing project.[36] Studies may be conducted individually ($n=1$), in groups (aggregations of $n=1$ individuals), or in systems (e.g., families, athletic teams, or workplace groups). For group studies, crowdsourced research collaborations, health social networks, and mobile applications are allowing studies to be conducted at new levels of scale and specificity, for example, having thousands of participants as opposed to dozens or hundreds.[37,38]

The ability to aggregate dozens of QS data streams to look for correlations is being developed by projects such as Singly, Fluxstream, Bodytrack, Sympho.Me, Sen.se, Cosm, and the Health Graph API.[39] Figure 3 shows a "mulitviz" display from Sen.se that plots coffee consumption, social interaction, and mood to find apparent linkage between social interaction and mood, although correlation is not necessarily causation.[40] The aggregation of multiple data streams could be a preliminary step toward two-way communication in big data QS applications that offer real-time interventional suggestions based on insights from multifactor sensor input processing. This kind of functionality could be extended to the development of flexible services that respond in real-time to demand at not just the individual level but also the community level. A concrete example could be using the timing, type, and cyclicality of 4 million purchase transactions that occurred during Easter week in Spain (http://senseable.mit.edu/bbva/) to design flexible bank, gas station, and store hours, and purchase recommendation services that respond in real-time to community demand.

Data analysis

Following data collection and integration, the next step is data analysis. A classic big data science problem is extracting signal from noise. The objective of many QS projects is sifting through large sets of collected data to find the exception that is the sign of a shift in pattern or an early warning signal. Ultimately, 99% of the data may be useless and easily discarded. However, since continuous monitoring and QS sensing is a new area and use cases have not been defined and formalized, much of the data must be stored for characterization, investigation, and validation. A high-profile use case is heart failure, where there is typically a two-week prevention window before a cardiac event during which heart rate variability may be predictive of pathology development. Translating heart rate data sampled at 250 times per second into early warnings and intervention is an unresolved challenge. One thing that could help is the invention of a new generation of data compression algorithms that could allow searching and pattern-finding within compressed files. Similar to the challenge of producing meaningful signals from heart-rate variability data is the example of galvanic skin response (GSR). Here too, data metrics that are sampled at many times per second and have been available for decades, but the information has been too noisy to produce useful signals correlated with external stimulus and behavior. It is only through the application of innovations in multiple areas—hardware design, wearable biosensors, signal processing, and big data methods—that GSR information is starting to become more useful.[41] Analyzing multiple QS data streams in real-time (for example, heart-rate variability, galvanic skin response, temperature, movement, and EEG activity) may likely be required for accurate assessment and intervention regarding biophysical state.

"THE OBJECTIVE OF MANY QS PROJECTS IS SIFTING THROUGH LARGE SETS OF COLLECTED DATA TO FIND THE EXCEPTION THAT IS THE SIGN OF A SHIFT IN PATTERN OR AN EARLY WARNING SIGNAL."

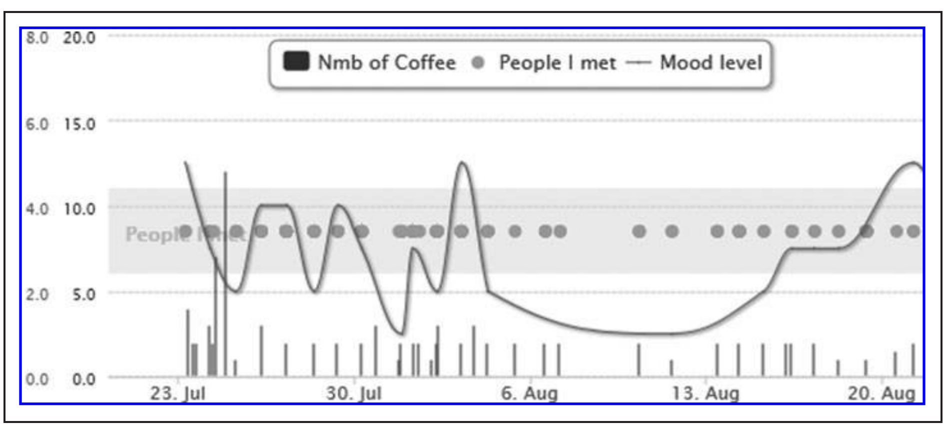

FIG. 3. Seeking correlations: multiviz data stream infographing available on the Sen.se Platform.[40] (Reproduced with permission from Sen.se)

Opportunities in working with large data corpora

In addition to the requirement for innovations in signal-to-noise and compression algorithms in working with big QS data, there are opportunities directly related to the feature of the information itself being big. Having large data corpora continues to allow for new methods and discovery. As Google has demonstrated, finally having large enough data sets was the key moment for progress in many venues, where simple machine-learning algorithms could then be run over large data corpora to produce significant results. Examples include spelling correction and language translation,[42] image recognition (getting computers to recognize pictures of cats),[43] and cultural anthropology via word searches on a database of 5 million digitally scanned books (http://books.google.com/ngrams).[44] Health generally and QS projects specifically could be an upcoming beneficiary of these methods, applying straightforward machine learning and other data analysis techniques to longitudinal personal data streams.

Large QS data corpora could lead to other forms of novel discovery in the areas of understanding baseline measures and variability in a variety of biophysical phenomena, and in creating new paradigms for pattern recognition. Given previous constraints, the traditional scientific research model focused on proving interventions from single snapshot moments in time, finding the delta between the starting point and ending point in the experimental versus the control group. Now in an era of low-cost big data, biological and other phenomena may be characterized more fully, longitudinally, and systemically. This feeds directly into the preventive maintenance approach to health as having quantitative data on large populations regarding baseline levels and normal variability could allow early warning signals to be more readily produced. With QS data for thousands and eventually millions of individuals, it could be possible to articulate new tiers of health norms with much greater granularity. A simple example is that it is unlikely that 8 hours of sleep per night is the norm for all people of all ages at all times. Continuous passive data collection could be translated into early warning alerts when certain biophysical behaviors shift outside of an individual's normal variability. Evidence in support of early warning signals as an approach to health maintenance is the finding that degradation in sleep quality and hemoglobin A1C levels have been shown to predict diabetes onset by 10 years.[45] Having this information ahead of time would be invaluable in deploying preventive medicine solutions.

Another dimension of novel discovery potentially enabled through QS data sets themselves being large is new categories of pattern recognition. Data can be reviewed in multiple paradigms related to time, frequency, episode, and other variables so that salient patterns that might not have been previously recognizable become obvious. There could be trends, cyclicality, episodic triggers, and other elements that are not clear in traditional time-linear data. An important foundational understanding of QS activities includes establishing longitudinal baseline measures of the internal and external elements of daily rhythms, normal deviation patterns, contingency adjustments, and emergent phenomena. These could be combined into a personal informatics climate with real-time ambient recommendations and early warnings. Big data analysis techniques could also be helpful in applying mathematical models from other fields such as turbulence, topology, chaos, complexity, and music to have a new look at resolving QS and other biological problems and investigate pattern universality more generally.

Big Data Science Leadership Opportunity in Defining Resources and Standards

In addition to there being opportunities for big data scientists to develop new models to support QS data collection, integration, and analysis, there are opportunities to lead in defining open-access database resources and privacy standards for how personal data is used. The establishment of public data resources and standards for their use could be a key step in galvanizing progress in the use of personal data. Public genome databases have greatly facilitated research efforts and knowledge development. Similar databases are needed for phenotypic data, where information in the order of a million participants is required for the realization of preventive medicine.[46]

Public databases

A precedent for public databases that are crowdsourced through open-access health-related big data projects is being established with projects like Harvard's Personal Genome Project (www.personalgenomes.org/) and the American Gut microbiome project (www.indiegogo.com/americangut). There is not yet a public access resource of user-contributed QS data but a data commons could be developed as a common repository where individuals could donate any variety of QS and other personal informatics data streams.[47] Data streams from diverse applications (e.g., Fitbit, Jawbone UP, Nike, Withings, myZeo, 23andMe genomic data, etc.) could be uploaded and aggregated with similar data from other contributors. Analogous to the Creative Commons licenses, there could be different tiers of user-selected privacy, use, and derivative-works permissioning. So far, there is at least one known database of QS data, the myZeo sleep data repository, available upon approval to researchers (www.myzeo.com/sleep/research-zeo). As another module of a QS Data Commons, it would be helpful to have an open-source repository of standardized questionnaire instruments used in academic studies to elicit information regarding personality traits, sleep, and behavior indicators (including instruments, results tabulation methodology, and user responses). Having questionnaires and responses on hand could greatly facilitate the conduct of experiments and aggregation of $n=1$ data into searchable community data.

The requirements for these kinds of data commons and public-access database resources could be minimal at the outset, with limited standardization or functionality. Currently operating in the absence of standards, vendors aggregating multiple QS data streams are using default protocols such as rich site summary (RSS) feeds and RESTful web services. Application designers too could use a common data export format such as JSON, with existing headers and access to the schema, including minimal metadata such as the device and model of the data source. Some more detailed technical concerns such as standards, formats, protocols, structure, metadata labeling, organization, and querying conventions could be addressed over time iteratively as the data commons grows and attracts funding sources. One next-order question is how to incorporate an experiment commons, a means of sharing experimental protocols and results. Further, the QS data streams need to be linked to healthy population longitudinal self-tracking more generally. This could be accomplished by having "health interest communities" that are the corresponding healthy cohorts to patient cohorts. Health interest communities could be a coordination feature in existing health social networks where individuals could be readily searched, profiled, and contacted for studies.

Data privacy

An increasing number of new personal data streams are being generated through quantified self tracking devices, biosensors, wireless Internet-of-things devices, health social network data, and social media data. Additional personalized data streams from consumer EEGs, eye-tracking, and emotion measurement could be coming in the future. It is necessary to think about personal data privacy rights and neural data privacy rights proactively to facilitate humanity's future directions in a mature, comfortable, and empowering way.[48] One helpful framework suggested by Kevin Kelly, a thought leader in the quantified self movement, is that of rights and responsibilities.[49] Health data streams would have attendant rights (for example, it is the contributor's right to decide how and with whom to share data) and responsibilities (for example, it is the contributor's responsibility to share data in any venue in which the individual is comfortable). One way that new standards are developing around the rights, responsibilities, and use of personal data is the example of the return of participant data, ideally with personalized recommendations, becoming the norm in community health research studies.[50]

"ADDITIONAL PERSONALIZED DATA STREAMS FROM CONSUMER EEGS, EYE-TRACKING, AND EMOTION MEASUREMENT COULD BE COMING IN THE FUTURE."

Health institutions are required to protect the privacy of health data, but individuals are free to share their own data and post it publicly. Many individuals are not comfortable with sharing their data, but those that are can contribute their data to create a valuable public good that is usable by all (similar to the Wikipedia, where less than 1% contribute to create an open public good). An encouraging example has come from the consumer genomics field as 76% of 23andMe subscribers indicated a desire to use their data to participate in research.[51] Also encouraging is that there has been a destigmatizing influence on genomic health issues as individuals having their own data realize that this is not a "Gattaca-like world" where there are some genetically perfect individuals. Rather, in reality, each person is likely at risk for one of the top twenty disease conditions such as cancer, heart disease, and diabetes. A broader range of health and behavior issues, particularly related to mental health and other current areas of taboo, could be similarly destigmatized and resolved through an open data commons of contributed data. The issues of the many can be inferred from the data of the few.

How Quantified Self-Tracking is Defining a New Kind of Science

There is a critique that self-tracking is not science, and this critique might be true if a narrow definition of science is considered. However, what is emerging is the notion of a much broader ecosystem in terms of what constitutes science. This spectrum includes professional scientists at one end of the continuum and citizen scientists, health social network participants, and self-trackers at the other.[52] Pertaining to big data directly is Kaggle, a crowdsourced data competition website who boasts the largest group of worldwide data scientists (60,000), a much higher number than those officially employed in the field.[53] The site recruits individuals with relevant skill sets to compete in finding solutions to big data challenges posed by real customers. This is one example of an Internet-based crowdsourced resource supplementing traditional science methods. Likewise, participatory QS health initiatives are extending the reach and capabilities of the traditional public health system.[54]

QS activities are extending and benefiting the public health research system in several ways. First, QS activity often consists of rapidly iterating through a number of low-cost experiments that can adaptively test a far greater combinatorial landscape of problems and solutions than would be feasible in traditional randomized clinical trials (RCTs). Second, the sheer numbers (on the order of millions) required for new public health endeavors such as preventive medicine require the large numbers of participants afforded by crowdsourced QS models. Third, QS activity is serving as the "venture capital arm of health research" by helping to surface new ideas and solutions that might then warrant the cost and effort of traditional studies. Fourth, QS activity is helping to stratify the public health research ecosystem by defining multiple nodes extending from traditional RCTs to earlier-stage discovery in professional studies run in crowdsourced cohorts, participative studies run by health social network members, and $n=1$ QS experimentation. The attitude of professional scientists is shifting too, from the dismissal of any nonprofessional activities to an interest in partnering with and adopting innovations from self-trackers and crowdsourced study operators like PatientsLikeMe, 23andMe, DIYgenomics, and Genomera. QS activities constitute a valuable new kind of research method and data resource with opportunities to apply techniques from a variety of other fields including biology, big data, computing, statistics, and sociology.

Quantified self and scientific soundness

Many self-trackers, both laypersons and professional scientists, consider and address issues related to the scientific soundness of projects. Self-trackers are extremely aware that $n=1$ experiments are a new kind of activity and many seek ways to improve the accuracy of results. Quantified self experimentation is interesting as a new phenomenon in science. The existing paradigm for scientific research was developed in an era when it was difficult and costly to obtain large amounts of data from large numbers of people and reorganize and select cohorts at will. One issue is that the generalized cohort in which a study was completed may not be representative in the correct way to any individual. It is known that many prescribed drugs are ineffective, perhaps half,[55] ergo the notion of personally tailored medicine, which is eminently more possible to implement in an era of big health data. Experimental accuracy is of persistent discussion within the quantified self community; for example, a separate meetup group formed specifically to focus on QS Experimental Design, and a special August 2012 meeting focused on data-science-related issues such as correlation, validity of tests and assessments, measurement error, and normalizing data (www.meetup.com/quantifiedself/events/71948532/).

> “MANY SELF-TRACKERS HAVE FOUND IMPLEMENTABLE SOLUTIONS IN AREAS THAT THE TRADITIONAL HEALTH SYSTEM WOULD NEVER HAVE STUDIED OR APPLIED TO THEIR SPECIFIC CASE.”

The principle objections to the scientific soundness of self-research include the small sample size of $n=1$, studies not being randomized or blinded, the inability of the experimenter to be objective, the problematic aspects of self-reported data, the difficulty of controlling for environmental and hereditary variables, the lack of precedents and models to help in the conduct and understanding of self-experimentation, the possibility that results are only a hypothesis, and the potentially confounding influences from known experimental dynamics such as the placebo effect and the Hawthorne effect. Of these, the issue of the experimenter’s inability to be objective includes other biases such as experimenter expectations, confirmation bias, peak-end bias,[56] overconfidence or optimism bias, and loss aversion. To address some of these biases, a QS study protocol has been designed to investigate overconfidence and loss aversion (inspired by these themes in the book *Thinking, Fast and Slow*)[57] in a crowdsourced study.[27]

Necessarily overgeneralizing, the main QS response to scientific-soundness objections is an interest in understanding and resolving these issues to the extent possible within the greater goal of having accurate self-experimentation methods and results. While randomized clinical trials are the gold standard for the evaluation of medical treatments, this level of rigor may not be required for all QS activities, and specific experimentation tiers with corresponding standards could be defined, possibly inspired by other tiered proof structures like the Oxford Centre for Evidence-based Medicine’s 10 Levels of Evidence (www.cebm.net/index.aspx?o=1025).

Standard practices are already starting to evolve organically in the dynamic QS experimentation field, and these could coalesce into different proof tiers as well. Where self-experimenters would like to improve scientific rigor, there are some solutions, for example, implementing a randomized blinded format where an independent third-party is asked to package test and control samples, or using a sequential methodology where an individual tries different interventions iteratively as in the DIYgenomics Vitamin B-9 and MTHFR Variants Study.[33] Wearable electronics and biometric sensors could allow for the possibility of greater objective data collection, which would help to address issues with self-reported data and experimenter objectivity.

The placebo effect is itself an interesting potential focal point for QS studies. Self-trackers have wondered if perhaps they will not be able to realize the benefits of the placebo effect if they are knowingly capturing data and aware of the intervention they are testing. Research has found that patients knowing they were receiving a placebo still produced a placebo effect that was about 20% more effective than no treatment,[58] and it would be interesting to examine this in a QS study. Further, it would be useful to try to quantify the size of the placebo effect, and define more specifically how it arises. Overall, it can be concluded that QS experimentation, despite perhaps not always fully conforming to scientifically sound methods, may be providing personally relevant outcomes that result in useful improvements to individuals’ quality of life. Many self-trackers have found implementable solutions in areas that the traditional health system would never have studied or applied to their specific case. In fact, one surprise from QS studies is how personally meaningful they have been, taking the personal statements from DIYgenomics study participants as an example.[33]

Limitations to the Widespread Adoption of Quantified Self-Tracking

Despite the potential benefits of quantified self-tracking, there are barriers to widespread adoption, which can be categorized into two levels: practical and mindset. First, considering the practical perspective, self-tracking could shift more to the mainstream if it were automated, easy, inexpensive, and comfortable. One factor that could make the biggest difference is automated (e.g., passive) data collection. No matter how easy, fun, social, and gamified QS vendors have tried to make self-tracking, the data collection is still primarily manual. The presence of financial incentives could also produce greater adoption in self-tracking. An analogy is available from energy usage, where studies found that having access to tracking data reduced electricity consumption by 10% and by 30% when financial incentives were added.[59] In the United States, where employers bear a significant portion of healthcare costs, there is motivation for cost reduction, and a link to health self-management and healthcare costs. Programs like Safeway's Health Measures, paying employees to stay at the same or lower weight on an annual basis, have been successful[60] but have not spread. It is hoped that the insurance exchanges to be implemented in 2013 will force more price rationalization into the U.S. healthcare system and encourage more personalized health self-management.[20] QS device data could be helpful in quantifying potential savings and verifying user behaviors. Incentives need not be exclusively financial, social support and a sense of community arise for some individuals via participation in online health social networks and could encourage QS-related behaviors. Regarding comfort and usability, QS devices are starting to become more unobtrusive and attractive for mainstream adoption. Plastic wristbands and smartwatches are becoming an aesthetic standard in wearable self-tracking electronics. This is a welcome advance from the semi-cumbersome aspects of earlier generations of biosensors like heart-rate monitor straps and the myZeo headband unit. In brain-tracking, second-generation consumer EEGs (Interaxon, Axio) are providing wearable headband alternatives to first-generation hard-plastic headsets (Emotiv, Neurosky).

> "THE CYCLE OF EXPERIMENTATION, INTERPRETATION, AND IMPROVEMENT TRANSFORMS THE QUANTIFIED SELF INTO AN IMPROVED 'HIGHER QUALITY' SELF."

Aside from practical issues, there are QS adoption issues related to mindset. These issues may be deeply cultural, philosophical, and sociological, but initial progress can be made from a marketing perspective. Many individuals are not interested in health and find self-tracking to be an alien concept. Health is still perceived as the responsibility of physicians, and health-related information is thought to be deterministic, negative, and unwanted. Value propositions must be constructed for different consumer audiences to articulate the utility of QS activities. One successful example is the Global Corporate Challenge (www.gettheworldmoving.com/), who with a simple pedometer and basic infographics (e.g., "you have walked from London to Mt. Kilimanjaro," aggregating activity over some time period) has enrolled nearly 200,000 corporate employees in the simple challenge of taking a certain number of steps each day. The success is due to the device being extremely easy to use ("the Twitter of self-tracking") and socially connective with the self and coworkers in just the right lightweight competitive way.

The Short-Term Future: The Quantified Self Becomes the Qualified Self

One important aspect of self-tracking is that it already links the quantitative and the qualitative in the sense that QS activity fundamentally includes both the collection of objective metrics data and the subjective experience of the impact of these data.[61] Self-trackers have an increasingly intimate relationship with data as it mediates the experience of reality. In self-tracking, individuals are performing studies and then applying results to improving their quality of life. The QS experimenter is simultaneously participant, practitioner, and beneficiary of studies. The cycle of experimentation, interpretation, and improvement transforms the quantified self into an improved "higher quality" self. The quantified self provides individuals with means for qualifying themselves, through which some level of performance may be attained or exceeded. This is one way in which quantified self leads to the qualified self. Two other ways that the quantified self is becoming the qualified self—by applying QS methods to the tracking of qualitative phenomena such as mood and by understanding that QS data collection is just the first step in creating qualitative feedback loops for behavior change—are discussed in the next section.

Next-generation QS: Quantifying qualitative phenomena

Self-tracking 1.0 could be conceptualized as the tracking of basic easily measurable quantitative phenomena such as steps walked, hours slept, and nutrition and exercise regimens. Self-tracking 2.0 is now becoming *au courant* in the tracking of qualitative (subjectively assessed) phenomena such as mood, emotion, happiness, and productivity. The contemporary trend in establishing tracking mechanisms for qualitative phenomena like mood has two main methods: either the self-tracker enters qualitative descriptors like words to monitor activity or enters numbers where qualitative phenomena have been modulated onto quantitative scales (e.g., my mood today is 7 on a 10-point scale).

In other cases, there is the significant big data challenge of mapping quantitative biosensor data onto qualitative human labels, for example, translating EEG signals into behavioral and emotional states. One project successfully mapped EEG brain signal data (using both the consumer-available Emotiv and lab equipment) onto a standard four-quadrant diagram of the key emotion variables of arousal and valence (which reflect the intensity and positive or negative charge of experiences).[62] This project is exemplar of the general frame of self-tracking 2.0, where both quantitative and qualitative data may be collected with the objective of improving quality of life in areas such as happiness, well-being, goal achievement, and stress reduction. The trend toward quality-of-life tracking is encapsulated in the idea of the "lean hardware movement becoming the lean heartware movement." Here "lean heartware" has the double meaning of being both lean hardware (i.e, inexpensive, easy to use) to measure the electrical activity of the heart (i.e., ECG) as it relates to physical state and pathology and also hardware and software to measure the qualitative aspects of the heart like the human subjective experience of emotion and well-being. Table 3 lists a range of well-being QS measurement tools.

Table 3. Quantified Self Tools for Quality of Life-Tracking and Sharing

Category and name	*Web site URL*
Happiness tracking	
Track Your Happiness	www.trackyourhappiness.org/
Mappiness	www.mappiness.org.uk/
The H(app)athon Project	www.happathon.com/
MoodPanda	http://moodpanda.com/
TechurSelf	www.techurself.com/urwell
Emotion tracking and sharing	
Gotta Feeling	http://gottafeeling.com/
Emotish	http://emotish.com/
Feelytics	http://feelytics.me/
Expereal	http://expereal.com/
Population-level emotion barometers	
We Feel Fine	http://wefeelfine.org/
moodmap	http://themoodmap.co.uk/
Pulse of the Nation	www.ccs.neu.edu/home/amislove/twittermood/
Twitter Mood Map	www.newscientist.com/blogs/onepercent/2011/09/twitter-reveals-the-worlds-emo-1.html
Wisdom 2.0	http://wisdom2summit.com/
Personal wellbeing platforms	
GravityEight	www.gravityeight.com/
MindBloom	www.mindbloom.com/
Get Some Headspace	www.getsomeheadspace.com/
Curious	http://wearecurio.us/
uGooder	www.ugooder.com/
Goal achievement platforms	
uMotif	www.uMotif.com/
DidThis	http://blog.didthis.com/
Schemer	www.schemer.com/ (personalized recommendations)
Pledge/incentive-based goal achievement platforms	
GymPact	www.gym-pact.com/
Stick	www.stickk.com/
Beeminder	www.beeminder.com/

QS data as an input to qualitative feedback loops for behavior change

The second point about the quantified self becoming the qualified self is the distinction that while data gathering may be quantitative, the use of these data is often qualitative. There may be little purpose to self-tracking if there is no feedback loop connecting it back to real-life problem solving and behavior change. Quantitative data collection is just the first step in a bigger process that then uses the assembled data to generate meaningful insights that engender some sort of action-taking as a result.[39] Since most humans are not good at thinking statistically (i.e., quantitatively), but are good at thinking in stories (i.e., qualitatively),[63] some of the most effective QS devices could be those that include dimensions of both, for example, that have quantitative accuracy and qualitative meaning-making functionality. Products could have one layer of quantitative data and statistical methodology that is then translated upstream to another tier where individuals can use the data to create narratives that relate more directly to their concerns. For example, there could be a mobile application (perhaps on augmented-reality glasses such as Google's Project Glass) in which citizens report their emotional reaction at seeing a pothole while automatically logging its location.[64] Emotional tags could be aggregated and linked to economic repercussions such as potential home-buyers checking the "emotional history" of a neighborhood together with its crime history and the quality of school districts.[64]

Effective human–computer interaction interfaces, and likely *de novo* interface creation, is important in supporting the further development of QS activity. An example of vendors having defined a new category of interfaces that are both quantitatively accurate and qualitatively meaningful is in personal genomics. Companies like 23andMe, deCODEme, and Navigenics provide intuitive online displays of ancestry profiles, statistical risk probabilities for disease, drug response, and athletic performance predisposition. Similarly, contemporary QS device vendors are charged with the challenge of making QS data sets accurately understandable and meaningfully actionable. User interfaces should allow self-trackers to create narratives, meaning, and insights from their quantitative data. One important outcome of big data QS is the empowerment of the individual through an intuitive understanding and ongoing interaction with their data. Data is democratized from scientific practices and made universal and meaningful for use by all individuals.

The Long-Term Future: The Quantified Self Becomes the Extended Exoself

Kevin Kelly, a quantified self community founder and thought leader, has articulated an interesting perspective that the current moment of self-quantification is merely an intermediary step toward something else—the future self. This future self is one that is spatially expanded, with a broad suite of exosenses—the exoself.[49] In fact, self as a concept is a trope that has only arisen recently in the scope of human history, perhaps evolving in lockstep with the sizeable and complex cultures of modernity.[65] The concept of the self continues to shift as individuals react to changes in culture and technology. QS activities are a new means of enabling the constant creation of the self. Further, there is now the notion of the extended connected self in the sense that individuals are projecting their data outward onto the world (e.g., mobile phones and other devices continuously pinging location and other data) while data from the world is projected back onto the individual (e.g., network nodes notice movement and communicate personalized information). Mobile phones, wearable computing, and other technology tools are tracking devices used both by humans and the ubiquitous data climate. Data quantification and self-tracking enable capabilities that are not possible with ordinary senses.

> "DATA IS DEMOCRATIZED FROM SCIENTIFIC PRACTICES AND MADE UNIVERSAL AND MEANINGFUL FOR USE BY ALL INDIVIDUALS."

Exosenses and the fast-approaching era of wearable electronics

The already ubiquitous data climate may be intensifying even more in short order. A completely new era in personal computing could be approaching in the form of wearable electronics. One impact could be that finally the *automated* tracking of many more kinds of quantitative and qualitative data would be possible. Significantly more individuals might engage in QS activities if it were easier, cheaper, and above all, automated. At present, the vast majority of individuals worldwide (85%) have cell phone access,[66] and1 billion have smartphones.[67] Mobile phones and tablets have been the most quickly adopted technology platforms to date,[68,69] and the wearable computing platform (e.g., smartwatches, disposable patches, augmented eyewear, etc.) could have even faster adoption. Cell phones are QS devices, and wearable electronics are even more deliberately a self-tracking platform. Wearable electronics could facilitate automated self-tracking as vast amounts of data are uploaded to the cloud for processing by millions of agents (i.e., normal individuals) going about their daily lives. The QS data ecosystem could include wearable electronics paired with mobile phones and cloud-based big data services so that the individual's continuous personal information climate could provide real-time performance optimization suggestions.

QS activities in the ubiquitous data climate make new kinds of interaction with the self, others, and the environment consciously and unconsciously possible. The Japanese concept of shikake (http://mtmr.jp/aaai2013/) is one example. Here, physical objects are embedded with sensors to trigger a physical or psychological behavior change. Another example is digital thermostats linked with QS body temperature sensors that could automatically adjust room temperature. Per Kevin Kelly, part of the value of quantified intermediates for human senses is that they too are networked—made smarter, visible, and sharable through big data processing.[49] For example, we may have some vague sense of our heart-rate variability and blood pressure levels but not much visibility. These metrics could be turned into haptically available exosenses that make the data explicit as it is communicated to individuals or communities.

Some of the most basic examples of exosenses, or wearable electronic senses, are augmented-reality glasses and haptics, some of which are already available. There is a wearable device that gives haptic (i.e., touch-based) feedback as to where the direction North is per a locational vibration in a worn electronic device. Another example is LEDs that blink in time with heartbeat, as sensed by a Polar chest strap (Eric Boyd, www.rtbot.net/sensebridge), or other biometric data such as smiles (Nancy Dougherty). Haptics is not the only exosense delivery made available; metrics like heart-rate variability, blood pressure, galvanic skin response, and stress level could be made explicit via audio, visual, taste, or olfactory mechanisms.

Another example of exosenses is memory augmentations like Memex, a thinking diary project developed by Mark Carranza[70] after being inspired by the concept proposed by Vannevar Bush in 1945.[71] Carranza has logged more than 1 million ideas since 1984 in a connected and easily accessible manner, and where tool and user have become inextricably linked in the process of cocreating reality. Self-experimentation too could be considered a form of exosense: the ability to modularly conceive of and test interventions in resolving a personal data problem. The next level of data literacy could be thinking, simulating, and visualizing different potential pathways, developing an extended sense of different potential versions of one's future self per different interventional paths, possibly with layered probabilities and contingencies. Sensing optimization pathways could be a relevant future exosense.

The extended exoself may have unprecedented regulation and control capabilities. Once equipped with QS devices, an individual body becomes a knowable, calculable, and administrable object.[72] Exoself technology could be a sort of fourth-person perspective[73] that facilitates the conveyance of humans into a new realm of extended self and eventually into different groups of joined selves. There is a paradox that on the one hand humans are becoming increasingly dependent upon technology for everything including interacting with the outside world, while on the other hand technology is providing a richer, more detailed, controllable, and personal relationship with the world.[74] Ultimately, QS exoself technology is helping to catalyze progress toward a more advanced future society by increasing the most vaunted of human commodities: choice, understanding, consciousness, and freedom.

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Address correspondence to:

Melanie Swan
MS Futures Group
PO Box 61258
Palo Alto, CA 94306

E-mail: m@melanieswan.com

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