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Data Aggregation as Social Relations: Making Datasets from Self-Tracking Data

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Data aggregations are an under-acknowledged site of social relations. The social and technical specifics of how data aggregate are arenas for rich debates about how knowledge ought to be produced, and who should produce it. Consumer goods such as fitness trackers create conditions where data scientists or professional researchers are no longer the only ones making decisions about how to aggregate data. Users of these products also rework their data to discover something medically significant to them. These practices call attention to a modality of 'scaling up' datasets about a single person that is different from, and until recently largely invisible to, clinical approaches to big data, which privilege the creation of a 'bird's eye' view across as many people. Both technical questions how to build these aggregations, and social questions of who should be involved, betray broader epistemological issues about how new knowledge is created from electronic devices.

Introduction

I am an applied anthropologist who has been conducting research in the Quantified Self (QS) community since 2012. I am also part of a technical research team prototyping software for synthesizing and exploring personal data, such as steps taken or air quality exposure. Finally, I am also an active self-tracker who participates in the QS community. In this article, I use these multiple positionalities to think through the social and cultural politics of data aggregation.

The practices of self-tracking within QS raise broader questions about what data aggregation means from a social perspective. QS is a community of people who keep track of their activities or bodies using a variety of technologies, such as handwritten logs, spreadsheets or electronic sensors. Some keep track of biomarkers by testing blood, saliva or microbiome outside clinical settings. Importantly, QS is also a community that meets online and in person, and has its own sociality and solidarities.[1]

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It does not include anyone and everyone who uses a fitness tracker. In some ways, the participants are quite elite. It is a community that originated in Silicon Valley, and skews white and highly educated, but in other ways it plays the role of the subaltern to more powerful actors in medicine and in technology production. This multivalent status makes QS an interesting site to think about who aggregates data and how.

In the social scientific literature on big data, data aggregation is often synonymous with relations of inequality and dominance, where there are deepening divides between the data 'haves' and 'have nots'.[2,3] This research points out that big data enables powerful actors to accrue even more power by taking advantage of information asymmetries through 'black boxing' what they know about customers and citizens.[4] These actors often use data to subtly coerce people into actions they might not otherwise take, or persuade them to think in terms limited by those who have designed data systems.[5–8] In the context of medical and consumer wellness data, these problems are particularly acute.[9–12] Armed with the authority of expertise, and the apparent objectivity of data, biomedical models of health dominate popular Western understandings of the body.[13] While such power dynamics are undeniable, recently some scholars have called for more expansive accounts of agency. McCarthy, for example, notes that digital skills, identities, and other cultural factors make any 'big data divide' more complex than it might at first seem.[14] Citizens and technology users might in fact exert new kinds of agency through data, even within larger limitations set by social systems.[15–17] Indeed, much of the critical scholarship on self-tracking examines the forms of agency that users of digital health technologies do have, even in the face of other kinds of domination.[1,18–23]

While this literature has sometimes focused on large-scale institutional arrangements, and at other times on everyday uses of technology, Taylor has pointed out that the social and technical specifics of how,[24] where and why data gets aggregated has been relatively under-examined. What choices are made in reducing data? Why is some data fused with this data, but not that? Science and technology studies (STS) has long pointed out that such choices have both social and technical origins,[25] but the full consequences of these socio-technical choices have not yet been fully fleshed out. The work of Lury and Gross has made important recent progress here, observing how big-data-style approaches to inflation calculations exposed a web of social relations between economic actors enacted in processes of calculation, or what they call a 'calculative infrastructure'.[26] Outside the big data literature, there is a rich anthropological history of thinking about calculation and measurement as a kind of social process, whether as generative social grammar[27–29] or as a means of conducting relations between institutions and citizens.[30,31]

Like Taylor, I argue that the specific practices involved in aggregating data contain the potential for many different kinds of social relationships, whether of dominance or agency exerted 'from below'. By following individual data points slowly as they accrete into something that could be called a dataset, we can see multiple kinds of politics, multiple social imaginations, and multiple epistemics concerning 'health'. I wish to extend the body of work discussed above by drawing a distinction between data that pools within one person versus across a population. Large datasets can be

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aggregated even within one person, by pooling together datasets across many different data types, time periods, or locations, and it can also be aggregated across many people. These aggregations might be built by individual technology users who cobble together information from many devices ad-hoc, or they might be done within large, complex infrastructures that optimize some forms of aggregation at the expense of others. These specificities matter in shaping how social power is created, reinforced, or subverted in data-centric societies.

My main argument is that the practices in QS, and the dilemmas faced in building technical infrastructures for self-trackers, call attention to an important scalar move that is different from, and until quite recently largely invisible to, clinical approaches to big data, which privilege forms of aggregation that create a 'bird's eye' view across as many people. QS data practices, alongside the technical discussions that follow, raise questions about when the single case or the tendency across a population matters, and thus opens space for broader public contestation over who gets to define problems of the body, and how.

Such contestation matters politically, as questions of who participates in medical knowledge production has been a longstanding concern (see, for example Epstein[32]). They also matter epistemologically. Rob Kitchin,[33] in his exploration of scientific, social scientific and humanities use of big data suggests that there is a need within the academy to reflect more deeply on the epistemological implications of big data. Too much of the discussion about big data for research, he argues, reproduces old 'two cultures' divides that could be overcome by a broader embrace of reflexive and contextually-nuanced epistemologies across the disciplines. The direction Kitchin points toward is, in a sense, happening already. It is happening not necessarily where he expects but, in this case at least, in the nascent conversations between the Quantified Self community, medical researchers, and technology producers in academic, non-profit, and private sector institutions.

I will develop my argument first by describing what it is self-trackers in the QS community do, based on extended participant observation and interviewing in those circles. Through the notion of a 'hinge' I explore the dimensions of the data that they work with, and how those dimensions shape aggregations and their meaning. I then discuss problems of aggregating data beyond the individual by situating it in a discussion of the role of self-tracking in public health. I will weave into this discussion some reflections of the design dilemmas faced by the Data Sense project, a software research project I work on that has had to wrestle with these tensions. I conclude with some thoughts about how divides between formal, institutionally-sanctioned research practices and the research practices of self-trackers might be shifting in subtle but significant ways.

Medicine from Above and Below

Scholars have analyzed self-tracking in various ways: as a form of biopolitics,[10] as an embodied way of conducting mindfulness,[21] and as a way of forming 'data doubles'

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that facilitate reflection and curiosity.[18] Here I approach QS participants as scientific knowledge producers, as people who have something to say to scientists, even if only a small portion of them identify as scientists professionally. Dana Greenfield's notion of QS as a paraclinical practice is particularly helpful in understanding how these technology 'users' might also be scientific knowledge producers.[23] She argues that QS community members appropriate the tools of clinical practice for their own ends. For them, data might diagnose, but it might also create room for personal narrative, critical reflection, and paths of self-care that would not be otherwise available. For Greenfield, this appropriation constitutes a *paraclinical practice* – a practice that is in dialogue with clinical practice, but is not entirely commensurate with it. As Greenfield observes, 'By taking up the tools of medicine, but not its claims to expertise, this is medicine turned inside out . . . where members can reformulate the epistemic cultures of medicine and care' (Ref. 23, p. 128). Here, participants ask questions, with data, that professional medical researchers either will not, or cannot, ask. Paraclinical practices do not always yield data made tame by the clinical gaze, even if that data originated in devices that are sold by vague appeals to clinical authority about what is 'good for you'.

In the context of a paraclinical practice, data are relevant when they can speak to personal circumstance. By contrast, the shift towards standardization in medicine known as evidence-based medicine privileges what is knowable by reference to a large population.[34] Abstracted from any life as it is actually lived, evidence-based medicine seeks generalizability, and this in turn defines the data deemed relevant in particular circumstances. The emerging science of precision medicine takes evidence-based medicine a step further, by expanding the volume data referring to single individuals in order to personalize medical treatments.[35] An individual genetic or microbiome composition, for example, might be measured as a variation from the norm in order to customize treatment. In the popular press, QS and personalized medicine are talked about in the same breath, but the epistemologies through which they create person-level aggregations are often radically different. Both traffic in rich aggregations of data about an individual, but precision medicine knows what it knows always through an aggregate. Self-trackers, on the other hand, have a more circumspect relationship to other people's data, focusing primarily (but not exclusively[1]) on their own data.

In paraclinical practices, the ability to aggregate data across many sources, and reframe and reinterpret that data, is important. A good example of why can be found in Anne Wright's journey. Anne is a former NASA roboticist who grew too sick to work. She found herself in the position of having, as Joe Dumit puts it, an 'illness you have to fight to get'.[36] Bodily states that do not fit established diagnostic categories prove difficult to acknowledge or create treatments for in clinical medicine. Anne received a diagnosis that acknowledged the problem existed, but gave her clues to neither the cause nor solution. After all possible medical routes were tried, she turned to a combination of tracking diet, sleep and a whole lineup of daily activities to see if she could, in her words, 'debug the problem'.

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The notion of debugging is significant here. She talks about how when she was working on the Mars rovers there were no instructions for how to fix a rover, so when something went wrong you had to develop an instinct for how to figure out what the cause was. It is exactly those same instincts that she uses here, to both figure out what data to collect, and how to interpret it. She develops a loose sense for what might be going on, collects some evidence to explore it more deeply, reflects on it in relation to the bodily sensations she's experiencing, and adjusts. Her tacking back and forth between exploration and shoring up a hypothesis remarkably resembles the hybrid, reflexive practices of deduction and induction that Kitchin says will be increasingly necessary for doing science with big datasets.[33] As the late self-tracker and UC Berkeley emeritus professor, Seth Roberts, was known for saying, 'you can't falsify a hypothesis you don't have', meaning that data can play a role in generating one. Paraclinical practices put more squarely in view the aspects of scientific research – the trial and error, the deliberations about which path to pursue – that are rarely reflected in publication.

As much as Anne's process is researcherly, it is also remarkably ordinary. She has much mathematical skill at her disposal, and yet she has deliberately made the choice to use the techniques of observation accessible to most of us, and not more esoteric methods such as regression analysis or machine learning. For example, she took a picture of everything she ate, rather than recording calories and protein and so forth, because those pictures can be interpreted in more flexible ways, even if less amenable to mathematical calculation. Data were a way for her to pay attention, not a way to render scientific. Eventually, through trial-and-error, she worked out that it was vegetables in the nightshade family that were causing the debilitating symptoms, and when she stopped eating them she was able to become functional again.

In Anne's case, both the symptoms and the potential causes of those symptoms were being recorded. However, in self-tracking often the data simply evokes something else, something that is not being measured that only the persons themselves really know. This was the case with John, another self-tracker who was having difficulty sleeping, and who turned to self-tracking to work out what was going wrong. One of his sleep issues turned out to be surprisingly simple and revealed by a consumer-grade sleep tracking device. The device told him that he was partially waking up at precisely 3am for a short time every single night. This prompted him to think about what else could be happening at 3am. The precision was suspicious: bodies are not usually that regular, but machines are. He worked out that his computer, which sat in his bedroom, was set to back itself up at 3am, and its lights and whirring partially disturbed his sleep.

For people who turn to data to figure out a problem, what matters is not having a gigantic pool necessarily, but having the kinds of intra-personal aggregations that support the work of finding clues to phenomena that could very well lie beyond the data themselves. Based on these observations, the Data Sense project began formulating a research question: what does data aggregation software have to do to support the finding of clues when all the relevant factors might not be represented in the dataset directly? Software infrastructures shape the kinds of aggregations

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people can accomplish, and who can accomplish them: data do not just aggregate on their own. Even getting data from varying sources into the same visual field of view requires more technical skill than one might assume. Indeed, Anne informed our research questions at many levels, both by sharing her story with us and by inspiring us through her Body Track project, which developed open source software that made particularly effective use of zooming and time alignment (aligning two or more datasets together on the same *x*-axis) for exploring these clues in the context of health coaching. Like the Body Track project, our design work sought to ease some of these hurdles. We took a complementary approach, focusing on patterns that are conceptually simple ('what recurs on a Tuesday?'), but require reasonably high levels of data processing skill to find them.

Hinges, Certainties and Uncertainties

Patterns like a 3am recurrence may be idiosyncratic, but they do reflect a social existence, too.[18] Ballestero's notion of aggregate numbers as a 'hinge' (personal communication) is useful for thinking about the specific attributes of data aggregations that make it possible to trace data back into everyday life. While data is abstract in many ways, it also has visual or semiotic affordances that call a person's attention to the connection between numbers and personal experience, or collective patterning. A pile of data in a spreadsheet rarely contains good hinges – the eye that scans down a column or across a row is unlikely to encounter anything meaningful, unless it is one very large or small number that stands out in a sea of unremarkable numbers. But a dataset parsed and visualized is a different story. The range of highs and lows, the timing or location of when data were recorded and when they were not, all might bring the viewer out of the sensory world of numbers' semiotics and data visualization, and into memories about what those patterns suggest. A hinge is where the embodied experience that data come from is once again foregrounded by the viewer.

One important hinge in self-tracking data is temporality. Temporality is contained in the data itself – it has a time stamp. Time series data gain value not because they list numerical values, but because the value and the time stamp are put together. It is this combination that enables a consideration of what might not actually be present in the data at all, because people's lives also have temporal cycles which they can map back to the data. John, for example, had gone through a process of considering many different kinds of temporalities before he arrived at his cyclical pattern. First he looked at the duration of sleeping across a night, the time of day he lays down in bed, etc. All of these can be derived from the same dataset, but speak to different potential causes. Churning through each of these can be thought of as a process of following the hinges back into context that each temporal cycle points toward, knowing that it is uncertain which is going to reveal a clue. As Anne commented, 'what makes a good self-tracker is not the ability to do math, it's the ability to think in multiple time scales.'

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The time scales of self-tracking data are at once social, personal, biological and machinic. John's '3am problem' had to do with an intersection between circadian rhythms and machine rhythms. Social rhythms might also matter. If we look at data for something that occurs every Thursday, we are less likely to see weather-related causes, because weather does not respond to the workweek, but bodies do. Hinges might be found in aggregates that reflect recurrences, but they might be in durations, or notions of the present. I am wearing, as I write this, a smartwatch that is currently counting my movements, heart rate, galvanic skin response (GSR) and skin temperature. Once I might have taken my pulse occasionally after exercising, or at the doctor's office, now I not only have more data, but data that insert themselves into the briefest moment, and extend into the long term. I might look at my data on the watch in a split second. Sixty-eight beats per minute it now says, and I've got a whopping 3888 steps under my belt for the day. These temporalities are shaped through design choices about aggregation methods. The heart rate reflects the rate a split second before, but the step count is an aggregation across the course of the day, yet they are both strangely 'now'. 'Now' becomes intriguingly pliable, rooted in the material and semiotic qualities of data. In turn, many 'nows' build up a record that I have to decide when to end. If I wear the watch for a year, or five years, does that get me any more purchase on what I might want to know compared with if I wore it for a week? Some of these temporalities tap back into cultural politics of fast-paced living and so forth, but many are orthogonal to such concerns, or otherwise introduce their own logics.

These aspects of temporal aggregation shape the hinges that yield semantic meaning, but they also shape the infrastructure design decisions that must be made to aggregate data across types and sources, and across more than one person. These decisions force material certainties that are in tension with the semantic uncertainties of hinges. For example, my smartwatch samples heart rate roughly on a second by second basis, but when I export the data I only get minute-by-minute data. In some ways, this makes sense for technical reasons alone: second-by-second data becomes a very large, hard-to-handle file, and there are limited reasons why someone might want data that fine-grained. However, there has to be a method to go from 60 data points to one, and that method is based on an informed guess about the future use of data. This guess is made based on beliefs about the onward social life of data as much as its mathematical properties.[25]

My smartwatch averages data across a minute upon export, presumably because averaging reduces the probability that spurious sensor readings affect the dataset. Open data advocates would point out that this is reasonable if someone is looking to measure exercise, but if someone is trying to use heart rate as a proxy for stress, taking the maximum across that minute might have been a better choice. Spikes that happen in a fight-or-flight moment are potentially more interesting, and become muted in an average. As Gitelman points out, there is no such thing as serving up the 'raw' data: an average or a max reflects a choice about which social relations companies and customers believe themselves to be in – is it one centered on stress or exercise?[25] These choices are one reason some QS participants get very invested in

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debates about open access to data. Their epistemology is closely linked to contextual knowledge, and it grates to see companies who have no possible way in to that context make wrong guesses about appropriate data reduction.

While there is plenty of discussion at QS meetups about the motivation of companies that limit access to one's own personal data, at another level the facts of physical building always curtail roads not taken even when technology producers are trying to enable deeper exploration. This is so even in our own case. For example, when a user uploads data onto Data Sense, Data Sense offers a repertoire of possible temporal and spatial aggregations deliberately much broader than those found in most self-tracking apps, but that repertoire is still necessarily limited by our (hopefully grounded) assumptions about what is most likely to reveal clues about health. They are assumptions that will not hold in all cases.

Space, of course, plays a similar role in proliferating the hinges that connect data back to lived lives. Spatial aggregations make similar scalar maneuvers, and hinge onto semantically-defined places. In these ways, the emergence of continuous sensing in everyday life has created not just more data *points*, but vastly more spatio-temporal dimensions to think with. It is those dimensions that connect back to lived experience and meaning-making. In these various dimensions we find both deep uncertainties (which hinge is most likely to emerge where?) and concrete claims, built into software, about what kind of social life data are actually participating in.

Making Connections between Individuals and Populations

The hinges of temporality and spatiality foreground types of sociality that are very different from the socialities foregrounded in population-based frequencies. These point toward questions of how many people do or have what. In other senses, these two types of hinges are not that far away from one another, especially in data-rich societies. For some in the QS community, personal data are to be collected precisely when there is a tenuous connection with established population-based medical knowledge. For example, early in my research a self-tracker and MD told me: 'Clinical trials are great for figuring out the side effects of a drug for the first 500 people. The problem is, you could be number 501 and have a very different reaction.' For people like this MD, collecting data for oneself is a recognition that we are all, in a sense, number 501 in one way or another. The question then becomes about figuring out how to *relate* to the more general knowledge available. Working out what is 'healthy for me' is partially a problem of categorization (where do I fit in a population), but also one that admits the possibility that there might not be a fit, or a good fit yet.

In the medical research world, aggregates of personal data are often imagined through the lens of evidence-based medicine. People using consumer device data for medical research often use the concept of data donation to frame data exchange. The idea is that medical discoveries are more likely to be made when individual self-trackers donate their data to public health research, and that public willingness and

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goodwill towards medicine can sustain donation flows.[37] This language is used in efforts such as the Health Data Exploration project, a University of California at San Diego project to facilitate and broaden data donation. By putting notions of donation at the center, assumptions about the relationship between donor and researcher harken back to medical research practice, as opposed to peer-to-peer or community-based collaboration. It suggests that once data are donated, involvement between researcher and donor more or less ends, outside the obligation of medical researchers to preserve donor privacy and use the data in an ethical manner. It is the medical expert who is largely in charge of translating that data into meaning.

The data donation model of aggregation shapes significant technical infrastructures and institutions, by prioritizing some matters over others. For example, for-profit and non-profit entities such as Validic and Open mHealth now exist for creating standardized clinical definitions of data from consumer devices through metadata and defined schemas, in order to make data legible in clinical care applications and research application. While such organizations often do involve 'lead patients' in clinical definition, such work is nevertheless about making it possible to remove a measurement from any particular context. Another set of infrastructures that are cohering around data donation has to do with the technologies for transporting data from consumer devices into medical researchers' hands. Software such as Fitabase, Open Humans and Apple Research Kit broker data between wearables manufacturers and medical researchers. They do this by building the necessary interoperability between systems, and the security and permissioning procedures in ways that suit the requirements for privacy and informed consent in medical research. While some efforts do facilitate data giveback to research participants, the data flows here can exclude data subjects from playing the role of knowledge producer. In fact, at the time of writing, Apple Research Kit excludes researchers who do not have institutional review board (IRB) approvals, which some self-trackers note effectively bars citizen scientists or QS participants who lack access to a university researcher from using that tool.

Epstein's research on AIDs activists' role in producing new scientific knowledge – not just lobbying for more research, but *doing* research – shows clearly that paraclinicians working outside of formal research settings are vital for steering scientific production towards areas of greatest human need.[32] There are also occasions where a role for experts can be equitably carved out in a participatory manner. In my own participant observation research on civic groups using Data Sense for environmental health research, it became clear that peer-to-peer or community-based participatory research efforts sometimes seek professional researchers, who can keep study momentum going, and put options on the table for data collection and analysis that paraclinicians might not have been exposed to. In fact, these particular groups sought professional involvement while also asserting a strong say over what is important to research.

Formal research, regardless of who coordinates, also gives participants a social occasion, and a shared framework, that facilitates data sharing more readily than individuals simply acting on their own. Without a social context or coordination,

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inter-personal aggregation of individually collected data might not happen, or develop its own problematic social dynamics. The involvement of experts to cohere together an inter-personal aggregation does not *necessarily* reproduce the inequities that the medical anthropology points out between expert and layperson that too often result in summary dismissal of laypeople's claims. The assumption that experts *must* be involved, however, does speak to this history. Such inequities could very well get reproduced in the course of infrastructure development, where very difficult material tradeoffs can mean tactics to support large-*N* ways of knowing can also make it harder to see the new knowledge that could be gained from community-based or peer-to-peer approaches, or harder for paraclinicians to develop a view of what large-*N* datasets mean.

It is here where intra- and inter-personal aggregations offer different hinges or pathways into new knowledge applicable beyond a single person. For example, in a population-based aggregation, it is doubtful that an epidemiologist would look for cycles of computer backup because that does not (yet) constitute an epidemic. To the extent that objects that beep and buzz are increasingly in people's homes and do contain the capacity to disturb many people's sleep, there might indeed be a broader social pattern that John's recurrence evokes. But, should John's sleep data be combined with others', the temporal hinges in the cross-population dataset are likely too heterogeneous to even emerge as a hinge. John's 3am problem might be my 1am on Tuesdays problem: the connection is entirely invisible without the both of us sitting in a room together, or talking with the researcher. Indeed, Greenfield observes that if self tracking is a study of an *N* of 1, then an *N* of a billion is not the same thing as an *N* of a billon 1s.[23] Many *N*s of 1 do not point to the same phenomena as clinical trials, which come together through shared experiment design.

Infrastructures of Encounter

While the infrastructure design strategies for wrangling '*N* of 1' data into large *N* are beginning to emerge, it is less well explored what kind of aggregation infrastructures *would* take the computer backup seriously, alongside what John did to come to understand it, as a way into new knowledge about shared bodily issues. As designers, the Data Sense team speculated that if we are all 'number 501' in one way or another, it might be productive to make it easier to *relate* individual aggregations to larger-*N*s, by linking in the same infrastructure the intra-personal aggregation with the inter-personal one. We are exploring this direction for two reasons. First, it might make it easier for users to contextualize what they discover about themselves in terms of the patterns others experience, and second, it might provide a grounds-up way to corroborate and explore diseases and bodily experiences that do not yet fit established medical categorization, or might be entirely non-medical but still cause for concern. That is, such aggregations might not cleanly test or prove an epidemiological hypothesis, but they might in fact surface a hinge for generating one.

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This design path parallels the dialogues that already take place within QS. In QS meetups, self-trackers do take an interest in other people's data as points for comparison, or a resource for triangulation, without attempting to claim what is or is not healthy in general. So, for example, when John tells his story at a community event, others might look at what John does and test whether it is true for them, too. In this way, we speculated that Data Sense might offer participants views of *inter*personal aggregations as a resource to reframe or reconsider the stories that could be told in the *intra*personal aggregation. Another example comes from my own QS group in Portland, Oregon, where a self-tracker was complaining that the algorithm used by his sleep sensing device must be off, because there is just no way he could get below a score of 98% good sleep. Someone in the audience had been using that same device, and said that a person can indeed get below 98% – he gets 70 something percent most nights.

This approach of individuals relating to larger-*N* raises questions about who should be allowed to query the larger-*N*, and how. It was clear that participation in anonymous aggregation should be through an explicit opt-in. Beyond that, we postulated that Data Sense users should be able to access aggregates of anonymous data only if there is sufficient data in the set, and only if the viewer herself has made a contribution of some kind – that is, is a participant as well as an analyst. In turn, the system would share the results of that query with all the others in the pool so that they too have visibility into what it is they have just contributed to. This reverses the normal flow of data and knowledge, in that using John or Anne's data requires recognizing them as both data subjects and knowledge producers at the same time. As this is an early prototype, of course, we have no idea yet about whether these mechanisms bring value to researchers, whether clinical or paraclinical. Using data in this way is, however, one example of efforts now happening to build infrastructures in ways that recognize data subjects as also sometimes knowledge producers. To varying extents, Patients Like Me, Cure Together, and Night Scout, also take the view that new knowledge can come from outside a carefully controlled clinical trial. Each of these projects situates the role for formal clinical knowledge and data subject differently. Patients Like Me is heavily oriented towards clinical researchers working with data subjects, while Night Scout is an open source, grounds-up project for accessing glucose data done entirely by and for diabetics and their families.

One can readily see how patient movements, environmental health groups and others might use tools like these to tack back and forth between individual health issues and broader claims that 'it's not just me'. At an epistemic level, the situation is less clear. This is an encounter with the very epistemological approaches with which our user base also has a complicated relationship. While they think of themselves as 'number 501', many nevertheless think in relation to the first 500. That is a real philosophical tension that cannot simply be resolved through technical means.

As we saw with temporal aggregations, however, software systems do have to take a point of view even when the social reality is unresolved tension. For example, an inter-personal aggregation system needs to know what data are poolable with what other data. What happens when data are comparable, but not exactly

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'the same' data? If two users have tracked 'sleep quality' using different measurements, they might wish to make their efforts available to others in a way that tell a cross-population story. In interdisciplinary discussions of big data, metadata is often seen as the way of handling this problem, but the goal here is not to create a field of infinite commensurability through extended markup; the goal is to create a place where people can learn from one another, where data's hinges can be acknowledged as uncertain. There is not as yet an established method of handling this. Our project might be but one indication that further technical research, alongside social research, is required to build infrastructures that facilitate dialogue between *N* of many 1s and large-*N* ways of producing knowledge.

Conclusion: Shifting Dialogues between *N* of Many and *N* of Many 1s

I began this article with a sharp if coarse distinction between the styles of thought that seek to make large-scale, generalizable epidemiological claims through big data, versus those that seek to use rich datasets to define and resolve a context-specific problem. While this paper has examined the cultural, epistemic, institutional and technological tensions that persist between *N* of 1 aggregations and large-*N* research, they are not static. There are now nascent dialogues that rework or reimagine the social relations of data aggregation in new ways. Prompted by the growth of clinically-relevant nonmedical data, and a growing recognition of the importance of patient activism and health movements, both clinicians and paraclinicians are asking questions about who gets access to data aggregations, and whether self-experimentation should remain the practice of lay people only.

The Quantified Self Public Health Symposium is one telling site of such discussion. This recurring event is sponsored by the American health foundation Robert Wood Johnson, and is organized by QS Labs staff, who also provide organizational support for the Quantified Self community. Attendees include representatives from government, foundations, academic researchers, clinicians, self-trackers who have done *N* of 1 research, and technology producers in for-profit and non-profit sectors. I attended as both technology producer and as anthropologist who might contribute social scientific commentary to the conversation. Participation has been US-centric, but expanded in later years to include non-US perspectives and voices from underrepresented groups. Notably, this symposium annually takes place adjacent to the Health Data Exploration annual meeting, so that participants might more easily participate in both. These institutional arrangements indicate that the distinction I draw as an anthropologist between the aggregations of paraclinical practice and aggregations of data donation are not as sharply held by all participants involved. The reality is that people explore and inhabit different positions, bricolaging ideas and technologies in trying to figure out what this encounter might be for them.

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We can see this bricolage in the shifting terms of discussion across the three years this symposium was held. The live discussion was highly multivocal, with participants trying out various points of view in conversation. The sense of where the starting point of those conversations was, however, did shift. The first year was marked by clinicians' complaints that this or that consumer device was not clinically legible, and thus was poor data to be donated, while the second year involved a clinician who self-tracked to try to understand what it is like to be on the receiving end of the monitoring she prescribed, and a patient who quite movingly talked about serving on a medical research advisory board and for once not being treated like the token patient. By the third meeting, there were plenty of assertions that self-tracking might turn the evidence pyramid on its head, and that the individual case study might transform in ways that elicit better understanding than the current gold standard accepted by evidence-based medicine. This discussion did acknowledge the role for reflexivity and contextual knowledge, alongside more traditionally scientific epistemological maneuvers. Enough tentative consensus was formed for the symposium series to end with the announcement of the creation of a scientific journal devoted entirely to *N* of 1 studies. At the time of writing, the editors are trialing the viability of this journal by hosting a special issue in the informatics journal, *Methods of Information in Medicine*.

While this particular gathering is not representative of vast industries and professional fields as they intersect, it is notable that within three years, the assumptions underlying the discussion shifted significantly. This suggests, pace Kitchin,[33] that the emergence of big data is in fact creating conditions for an epistemological discussion about the situated reflexivity that big data systems make possible in new ways. In self-tracking, threads along these lines are indeed forming. Data can be marshalled for scientific validation, or for exploration, or for more humanistic concerns, by both clinicians and paraclinicians. The case of Quantified Self speaks to the possibility that significant epistemological discussions might flourish in the encounters between science and paraclinical practice – that is, the parts of society that value science enough to request that it act differently.

While the emergence of Big Data frames such discussions, the technical infrastructures are being shaped by these threads as much as the other way around. They are not just implementations of known ways to solve a problem, but engineering research efforts in and of themselves. The discussion of how data aggregate and for whom reinvigorates technical questions alongside questions of public participation in knowledge production. However, the social relations of data aggregations only become visible once we get beyond coarse notions of 'data haves' and 'data have nots' that serve as the starting point for much social scientific discussion of Big Data. They start to appear when we can identify with greater specificity what kinds of aggregations happen where, both in terms of the social configurations of the technical pipes – to whom does data go, and on what terms – and in terms of the uncertain semantic meanings of data aggregations, where hinges point toward new (and not so new) ways of imagining the social patterns we believe ourselves to inhabit.

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