What gets counted counts

Meet John

It's 2029. John wakes up at 06:30. He rolls over and sees Laura's sleep monitor softly glowing. 'Still sound asleep, currently in REM', he notices, 'She sleeps right according to the schedule of an 8-year-old.' He sighs reassured. He takes his cold shower, dresses up, takes his suggested breakfast, and kisses his husband Ludger goodbye and is ready to head to the office. As usual, Ludger will wake up Laura and bring her to school.

Today John opts for the bike, as the forecast doesn't show any rain or strong winds. He takes the route which is 2.6 km longer than his regular route, to get in that little extra exercise. Over the last weeks, he has noticed that on the days he gets more movement in the morning, his morning focus lasts longer and drops half an hour later than on the days he goes to work by public transport.

After parking his bike, he enters the building and goes through the security gates. Because he works at this high-profile company and the building holds 8000 employees, the security gate randomly chooses a visitor or employee to check their bags. 'Luckily they aren't programmed to do checkups too often so I can almost always just walk through!' John thinks.

John arrives 1 hour before most people because that is when he is most productive and finishes most tasks per hour. His desk is equipped with heuristics sensors, an eye-tracking monitor, a keyboard that tracks your typing intervals, speed & content, and an environment checker (noise, air quality, lighting, temperature, bacteria, etc.). So far, the setup has shown its benefits, as the system learns what tasks John prefers through reading his engagement, which is then used to divide tasks within his team on these insights.

He logs in through face recognition and is immediately given an automatically generated agenda and to-do list. He sets his devices and brainwave stimulator to 'deep focus', and gets right to work.

During his work day, he is casually reminded of stretches when he's been sitting for too long, coffee breaks when he is out of focus, and toilet breaks when needed. This helps him to be productive during the day, but also prevents his back problem from getting back.

When his blood sugar level hits 80, and his burned calories exceed his calorie intake of this morning, he is prompted to get lunch. "Already?" asks his desk neighbor Dennis, "You should eat more at breakfast next time!". '11:30?' thinks John, "You're right Dennis!", he says. He notes it down so that tomorrow he hopefully can get lunch with the rest of his colleagues.

Around 15:00, John receives another notification on his smartwatch; "Suggested social activity." John checks his pplkpr app [5] and chooses Kim, who is at the top of the list of people who make him most happy at the office. She has an incredible score of 78% happiness, whereas most of his colleagues are measured to make him mostly stressed, bored, or annoyed.

Next to this, the company has set up the shared goal of closer collaboration between colleagues, so employees are matched up for social-building activities more often.

At the end of the day, John receives his daily summary. He checks his productivity and fitness score and receives 10 points on his work credits. He is now at 9830, with only 170 left to get one tax bracket lower!

He leaves and goes by the Smith family to pick up Laura. They chitchat about her acrobatics lesson and her playdate with Mike, and reach home where Ludger has already started cooking. It's going to be quinoa tonight, inspired by the online sustainable food community Ludger is part of.
At dinner, they go over Laura's school day, and Ludger decides to check her performance dashboard. "Hey Laura, are you stressed about anything?" he asks. Ludger hands the tablet to John and points to the spikes in her heart rate during the day over the last weeks. Laura seems to get a little uncomfortable and stares at her plate. "You can tell us anything, Laura, we can't help you if you don't share it." John pushes. "It's mostly during your math lessons, I see." Ludger adds. "Are you having trouble with math, darling?"
Laura admits to having difficulties with the new subject and being nervous about the upcoming exam. Laura's dads try to soothe her and explain where she might be in the learning curve and how it will improve. They decide that it's best to share the data with the math teacher and to ask for a little extra guidance during the lessons.

After dinner, they play a game of NeuroQuest together. Then Laura is put to bed and John and Ludger both read for some time. Especially Ludger is reading often lately, he's trying to read up to 200 books this year, as part of his '365 hard' challenge. A little before 22:00, John asks Ludger to join him to bed, because both of them have to get up early again tomorrow. Before falling asleep, they snuggle up and end up making love. "Goodnight honey", says Ludger, when they settle down for good this time. John's smartwatch lights up one more time before he falls asleep. 'Nice', thinks John, 'cardio goal achieved.'

Quantifying for the Better

In the scenario I have just sketched, John illustrates a typical member of the Quantified Self (QS) community. People in this community seek "self-knowledge through numbers" by participating in self-tracking activities [9]. This lifestyle is promoted as one that increases commute health, improves the accuracy of diagnoses, and personalizes healthcare tremendously. Through QS practices, people are taking responsibility for their health. No longer are people dependent on their physicists to diagnose and advise them, but they become the diagnosers themselves, and are empowered with control [10].
Next to this, self-measuring tools allow for a broader and more contextual-rich form of data capturing. Where doctors before could only trust retrospective descriptions and judge on situated snapshots, smart sensors give a detailed peek into daily habits. This then opens up the possibility for a deeper understanding of relationships between habits and health issues, which allows for more accurate and fitting treatments [10].

In the fictitious scenario, we see this in John's life in several ways. We can see that John makes conscious choices and is very informed about his health. For example, John has found out that his morning activities influence his work performance later in the day. This insight could only be derived through the inclusion and interconnectivity of all his contextual data. He knows how to get the most out of his day (performance-focused), and makes choices accordingly [11]. Furthermore, John is able to make some choices that increase comfort, like taking the bike to work only when the weather is good enough. Data-informed decisions like this make him feel more secure about his choices and give him less bad results than if he would choose on instinct (even if it's as simple as getting wet).

All the sensors equipped at his desk and his long use of the systems, allow John to outsource his reminders, making it easier for him to do the things which he finds important and are good for him. All the simple and seemingly small things during the day, like when to stand up from your seat or when to have lunch, can still have a big impact. Regulating these activities and their cues increases comfort, but most especially creates a steady balance. Never again will John snap at his colleagues, just because he is hungry. Automating decisions also keeps him sharp during the day, as he prevents decision fatigue [1].

Looking at the situation at the dinner table, we experience the double-edged sword of the data dashboard of Laura. As a benefit, the control of Laura's data allowed the family to discover her difficulties with math in an early stage, and could potentially have prevented Laura from building a strong negative relationship with math, or her falling behind on the matter and having to redo the school year. Here, the data provided her parents with an insight that was not yet visible on the surface. Also, the combination of her heart rate and class schedule provided the context that was needed, to understand what caused her anxiety.
However, what it also illustrates is the surveillance John and Ludger have over Laura. This undermines a strong trustful relationship between the family, as Laura's troubles are 'discovered' through the data rather than shared out of comfort and trust. Furthermore, like this, John and Ludger do not learn to look at their daughter through her actual behavior. They 'know' Laura mostly through her data. And, is that what we want the future of parenting to be? Being a data analyst of your kids?

Measure Once, Think Twice

The dinner scenario between Laura and her parents shows a common pitfall of the QS; over-trust in data [11]. Some QS'ers even go as far as not trusting our human capabilities anymore. They believe data gives us an objective look at how things *really* are: "instead of thinking with our flighty, emotional, easy-to-manipulate brains, we'll be feeling with our rational, measurable, hard-to-manipulate guts" [12]. However, let's look at some things data and quantification *can't* do.

The desk setup of John, which reads his engagement through eye tracking, typing fluidity & content, and brainwaves, also causes some trouble. Over time, John will receive more and more of the same kinds of tasks, which limits him from exploring and learning new things. Having this task distribution automated also refrains him from thinking more in-depth about what he would like to do and why. The one-sidedness of his tasks can also eventually lead to boredom. Is lasagne still nice if you have it every meal?

With the desire to achieve the gamified goals, crush personal records, and to have complete datasets, tracking can become obsessive. This can drown out intrinsic motivations which were for

the activity itself with the motivation of doing it for the sake of having that data [11]. The "technology shapes what can be measured, therefore shapes what we care about." [6]
The scenario that ends in the bedroom left us wondering; did John have intercourse with Ludger because he really wanted it, or was he motivated by something else? What was of most value to him? If it were up to me, I would totally get rid of the smartwatch if that would mean that my partner gives me their honest, truly meant, and desired love.

In addition, over-trust of data also can take the role of self-fulfilling prophecies, where people internalize the view of the data [11]. Think about the pplkpr app of John [5]; once he sees someone is measured to leave him more often 'annoyed' than 'happy', what do you think will happen? Most likely, John will only find the person even more annoying.

Next to all of this, privacy is a very big issue in today's society as well [4].

Quantified Risks

So far, I have discussed the benefits and pitfalls of quantifying and tracking ourselves. However, these are just the effects directly experienced by the family in the scenario. What about all the things that happen in the bigger picture, or behind the surface?

In their book, D'Ignazio and Klein [3] introduce Data Feminism. While the term 'feminism' seemingly exclusively focuses on gender discrimination, the authors use the word to tackle inequalities far beyond gender. Their work illustrates the biased, cultural, and timely situated nature of data, but most of all, the general illiteracy when handling this data, and the practical effects its implementation has.
Building upon the work of multiple feminist data-scientists, D'Ignazio and Klein introduce 10 principles to handle data more inclusively; "(1) examine power, (2) challenge power, (3) elevate emotion & embodiness, (4) rethink binaries and hierarchies, (5) embrace pluralism, (6) consider context, and (7) make labor visible" [3].
They invite readers to question among other things who collected the data, when the data was collected, who was included in the collection, and what purpose the data was intended to serve.

"So what?" you might think."If I don't get a smartwatch, I don't have to deal with all of this, right?" Unfortunately, that is an illusion. You are already part of it; you feed the databases with your data and are judged through the algorithms built on biased databases.
You might not notice this yourself, which probably means you're benefiting from these systems, rather than being oppressed by them: the *privilege hazard* [3]. This happens for example with algorithms when "the data that shape them, and the models designed to put those data to use, are created by small groups of people and then scaled up to users around the globe." [3]
To illustrate this, D'Ignazio and Klein share the experience of Joy Buolamwini, who was working on a facial-analysis system. Her dark-skinned face could not be recognized by the software, while it had no problem seeing her lighter-skinned peers. She discovered that the dataset on which most facial-recognition systems are built contains 78% male and 84% white faces. Only 4% matched up with her heuristics: dark-skinned women. If you're white-skinned, you would have never experienced this problem, and probably also would not have thought about it either, because you don't experience it. However, the privilege hazard goes further than this; no developer, tester, or even user had detected the problem of Buolamwini before [3]. This illustrates two things: (1) the

people in power positions for these kinds of technological developments are mostly white, and (2) their data practices are not inclusive. And while the first mistake is already made with the training data of the software, these corporations apparently don't even test with accurately representative user groups either.

In the scenario of John, we see he experiences this privilege hazard at the security gates. Sure, *he* does not get picked out a lot for checkups, but he might be wrong about the reason behind it. 'Random' almost never truly means random. The scanner reads his heuristics and decides whether to check him or not. What data would the system be trained on? Maybe we can use the heuristics of the prisoners of Azkaban to train the data about 'suspicious' or 'potentially dangerous' people. But, who has put these people in prison, and, do they always give fair and unbiased treatment? John does not see the experience of others, like the possible dark-skinned or tattooed colleague who gets picked out at least once a week.

Next to the application of biased datasets, we should also think about how our technologies *feed* biases in the data [3]. In the scenario of John, this comes forward in for example the sleeping monitor device of Laura. You have probably just read over it, but have you thought about the type of households that make use of these types of systems? And what do you think the database that the device is using to compare Laura's sleep habits looks like? With this device, I dare to bet that the data is filled with children who grow up in wealthy families with very good sleeping conditions. However, that is impossibly an accurate representation of the 10-year-olds in the world. In this scenario, Laura feeds this bias even further. Being part of this wealthy family with loving and caring parents, Laura exactly lives by the privileged standard. Adding her data to the datasets of the sleeping monitor will just feed this unrealistic standard even further.

So, hidden in all of our actions and systems making use of data, we add a little something. Even if you don't notice it or are not aware of it, *you* participate as well. Your phone, social media habits, browsing activity, and official registrations all feed the data of this world.

From Quantified to Qualified

So, what do we think now about the story of John? Is this the future we want to work towards?
I believe we are very unaware players within the data economy we live in.
"[T]here is a misalignment between people's understanding and expectations of their data and their actual collection and use by product and service providers. It hampers people's rational understanding of their data and even more, of what data feels like." [8]. Most of us even "don't know what we don't know" [8].

Data Feminism is a beautiful start to sharing the true story of data, and provoking data scientists towards better data practices. I believe we should continue this and start with becoming aware, working towards a shared awareness. What are your labels? What groups of humans do you represent in the data? Who works with this data, and with what intent? [3]

But maybe that is not radical enough. Should we even want to live and work with so much data all the time? Maybe we should slow down the quantification and try to steer away from a data economy at all. Like Davis illustrates, qualification is always needed for quantification. They write that "the same raw data can take on multiple meanings with quite different behavioral and

perceptual outcomes." Therefore, qualitative sense-making is needed to understand our data, as it gives shape to our numbers [2]. So then, why not give it more credit?
Looking at our personal relationship with data, I believe there should be a change in attitude. We should change our trust in data by becoming more aware of its pitfalls, but most importantly, change how we look at ourselves. We are not systems that can be improved or perfected, we are *humans*. We are beautiful exactly because of our differences, spontaneity, and complexity. We should step away from working towards one conform, and embrace complexity and personality in each dataset [7]. We have to stop with valuing someone through their data, and have to start valuing someone for who they truly are. We should go from Quantified Self to Qualified Self.
Data is beautiful, but only when you treat it right.

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