

## 4 DATA EXPERIENCES

*February 25, 2017:* I have joined Jesper, my husband, at the optician's to check out some glasses that he had had put aside a couple of days earlier. At the counter, a friendly optician's assistant asks for his "CPR" – his personal identity number from the Civil Registration System. Happening to glance at the screen, I cannot help noticing the number of the previous customer. With the CPR number, she quickly retrieves my husband's record, where they have noted not only his optometric measures and previous purchases, but also the numbers of the spectacle frames that he found interesting on a previous visit. He could walk into any shop in this chain, Jesper tells me, and they would be able to look all of it up in seconds. The CPR number also links his purchases to his health insurance and bank, and can automatically allocate subsidies for any purchase even if he changes his address or moves to another bank. The Civil Registration System facilitates automatic updating (see chapter 2). Jesper loves the efficiency of it.

The woman quickly finds the frames and we step aside, discussing how he looks. They are not quite right for him. As we return the spectacle frames, I ask why they connect this commercial information to his state-sanctioned CPR number. It strikes me as a very centralized way of keeping track of people . . . for a shop on the high street. The optician explains that they are legally obliged to keep "patient records"<sup>1</sup>—and then adds that it is very important to log out of the system so that nobody sees the CPR number of the previous customer. I point out that they apparently forgot to do that when we arrived. She smiles gently and thanks me for alerting them.

Meanwhile, Jesper is stepping on his own toes, so eager is he to leave the shop. He practically pulls me out into the bright February sunlight, where

he explains how embarrassing that was. Why did I have to question the use of the CPR number? Why did I mention that I could see the number of the previous customer? I stare at him, surprised, and just as I am about to defend myself, I realize how I am in the middle of an ethnomethodological moment. In his introduction to ethnomethodology, Garfinkel (1984) spoke about experiencing tacit cultural rules by breaking them. Without deliberately deciding to do so, I have begun breaking rules about data practices—rules I did not even know existed. Having at this point worked for about a year trying to understand the politics of intensified data sourcing, I am now more and more often asking questions that make people feel uncomfortable. Jesper is not easily embarrassed: I think this is the main reason why I went home and immediately described the episode in my field notes. I was beginning to realize that the invisible data infrastructures that often make life in Denmark so seamless and “integrated” involve a particular social texture—a set of tacit assumptions—that demand attention if I am to understand the politics of intensified data sourcing. Assumptions about data are nested in intersubjective relations between the users of data, and they catch people’s attention only when somebody transgresses the social rules—as I did on this occasion. Data infrastructures thrive on seamlessness, on a sort of invisibility. While they cannot be observed as objects, we still feel what they do. We encounter them through interfaces. In these encounters, an analytical potential resides. This potential can be actuated when we think of data and data infrastructures as producing a bodily experience.

In this chapter, I argue my point about data experiences by presenting my own methodological engagement with Danish data infrastructures—that is, my own data experiences. I thereby discuss a number of my methodological choices, but the point of focusing on data experiences is not limited to methods. My discussion of methods serves as an entry point to understanding how the politics of intensified data sourcing reaches into intimate aspects of how humans understand the world around them.

Data infrastructures are not places you can visit, nor objects you can hold. They are inapproachable, or transient, field sites. Still, they work on us. They inform the sensory anticipation of data promises. They shape data living. They permeate data work. However, we see *how* they do so only when we are able to translate our personal experiences into tools of observation (Verran 2021). Academics like me, who study healthcare organizations and data infrastructures, as well as people working in the healthcare services

with data tools, have to embrace their own sensory experience to assess how those tools work. It is necessary to make well-informed decisions.

It is not easy to study data experiences. First, where are the data? At the optician's, I realized that features of my everyday mode of data living were opaque even to me. Service providers can access and use data about Jesper and me, but I do not know how, when, or for what purpose they do so. In what I called "wired medicine" in chapter 2, healthcare providers often see data instead of patients—data that can be read, stored, and exchanged by computers without the patient being present. Data work is thereby embedded in a basic paradox: data dematerialize interactions whereby data can be in many places at the same time and connect people and systems *at a distance*, while data simultaneously rematerialize interactions because they connect to people through *physical interfaces* (like data dashboards) and *embodied experiences* (like the one at the optician's). Data are used by people to affect other people, but this mostly happens through wires and computer interfaces. Datafication relies on interactions mediated by materiality. Experiences with hardware and software shape what people do and know. This mutual dematerialization and rematerialization constitute the first paradox that this chapter deals with, and this is important because the paradox involves methodological challenges relating to where to go and what to do when studying data.

There is a second paradox I will discuss in this chapter. It revolves around standardization. Data become successful through standardization, and yet they are never able to fully standardize human experience. The seamlessness that Jesper enjoys rests on standards. Standards are a prerequisite for systems to become integrated so that computers can communicate effortlessly with computers. Standards for integration are the reason why Jesper does not even have to inform his health insurance if he opens a new bank account: his identity number is linked to a primary bank account and automatically updated in all systems drawing on information from the Civil Registration System, the CPR. Yet standardization affects people differently. Each person experiences and reacts to data and digital interfaces in her or his own way. What stimulates curiosity for some creates embarrassment for others, as when I violated tacit rules at the optician's out of curiosity and embarrassed Jesper (and possibly the woman behind the counter). By talking about data experiences, I want to create greater awareness of the variation in how each of us engages with data in the course of everyday life.

Equipped with this awareness, it is possible to look for the experiential dimensions of data work in healthcare organizations. There is every reason for acknowledging data experiences, and yet it is as if there is no vocabulary for talking about them. I therefore begin with a discussion of what I mean by the term “data experience,” and then turn to examples of experiences emerging in relation to the types of data work discussed in chapter 3 (production, analysis, instruction, and use), each time beginning with reflections on my own data work—my methods—and then relating them to examples from the health services.

#### EXPERIENCE: BEYOND EPISTEMIC CONCERNS AND POWER CRITIQUE

Data are typically approached as epistemic objects (conveyers of information) or political objects (shaping relations of power and resource allocation). Consider, for example, the important work in anthropology, science and technology studies (STS), and critical data studies, where scholars question the *epistemic* assumptions found in policy discourses (Borgman 2015; boyd and Crawford 2012; Busch 2017), or criticize the *power effects* of data (Iliadis and Russo 2016), including power understood as pertaining to inequity (van Dijk 2020), infrastructural and cultural change (van Dijck, Poell, and De Wall 2018; van Dijck 2013), economic disruption (Hoffman 2018; Zuboff 2019), or the impact of data on issues like privacy (Taylor 2017; Obar 2017). I discussed this body of literature in the introduction. Although delivering fascinating insights, these approaches nevertheless pay limited attention to *direct experiences* with data. For these scholars, data experiences means the type of lives people live—their data living—as a consequence of data infrastructures (Ebeling 2016; Cheney-Lippold 2017; Kitchin 2021), not *how they experience data*. Even though these are important issues, the direct engagement with data and data infrastructures is black-boxed: data remain epistemic, political, or economic rather than *experiential* objects.

A few scholars have begun paying more attention to the way that data and data infrastructures can be experienced as beautiful (Halpern 2014), and how data aesthetics (color coding, graphs, interactive maps) mediate power effects by privileging particular representations and silencing others (Ratner and Ruppert 2019). They study how the beauty that data visualization experts like Edward Tufte strive for works on people (Tufte 2020). Others note how data provoke feelings such as “data anxiety” (Crawford 2014;

Pink, Lanzeni, and Horst 2018; Cool 2019) or “enchantment” (Smith 2018). Studies of self-trackers and patients who use various wearables and data tools illustrate how people respond emotionally to “seeing” their own data (Kristensen and Prigge 2018; Lomborg, Langstrup, and Andersen 2020; Oxlund 2012). Kristensen and colleagues, in particular, has emphasized how people relate to data goals, such as walking 10,000 steps a day or eating a certain amount of fruits and vegetables, without engaging with the scientific evidence supposedly guiding these goals (Kristensen, Jacobsen, and Pihl-Thingvad 2017; Kristensen and Ruckenstein 2018). Data work on the users, not as conveyers of truth but as partners they can interact with. Immaterial and diffuse goals become material when, for example, red turns to green in an app on your cell phone or when a pedometer makes a sound. Lupton (2020) similarly suggests that the study of self-tracking should be about “paying attention to practices, affects and sensory and other embodied experiences” (6), and she has also suggested that such affective dimensions might be relevant for health professionals (Lupton 2017; Lupton and Maslen 2017). I think these lessons about embodied experiences gathered from studies of self-trackers should indeed be used also to study data experiences among clinical staff—as well as among policymakers, administrators, researchers, and patients.

“Experience” is, I admit, a troubled and ambiguous word (Asad 1994). I use it to build a bridge to the phenomenological dimensions that are easily forgotten in epistemological and political debates about data. The phenomenological turn in anthropology and STS has already sought to attune us to the experiential aspects of technology (Gunnarson 2016; Jackson 1996, 2002b; Mattingly 2010). It draws on Merleau-Ponty’s phenomenology, which explored how people make sense of the world around them in a bodily conscious way (e.g., Merleau-Ponty 2002). People are not computers. They engage information as embodied beings, not just through logocentric analytical computations (Hastrup 1994, 1995).

As noted by Mauss (2007), the body is the primary instrument of any human being. Although emphasizing the body as the locus of experience, Merleau-Ponty (2002) also acknowledged the role of technology, noting how people can learn to experience through, for example, a stick as an extension of the body (175). Appreciation of technology as an embodied way of experiencing the world has been developed further in postphenomenology (Ihde 2002; Verbeek 2011; Olsen, Selinger, and Riis 2008; Selinger 2006). Today,

it is through data—processed and accessed through digital technology—that people engage many aspects of the world (de Boer 2020; Schwennesen 2019). With data, people learn to sense themselves and the world around them in particular ways (Torenholt, Saltbæk, and Langstrup 2020; Kragh-Furbo, Wilkinson, Mort et al. 2018). Digital data infrastructures not only convey information about the world, but they also make particular worlds emerge as experiential phenomena.

From a philosophical perspective, Sokolowski (2000) has argued the need for appreciating phenomenological experience also when exploring aspects of the world otherwise left to science (consider, for example, climate change) (see also Knox 2022). His point is that we cannot evade or circumvent the phenomenological dimension, even when wishing that people could analyze data as dispassionately as computers:

We could not live in the world projected by science; we can only live in the life world, and this basic world has its own forms of truth and verification that are not displaced but only complemented by the truth and verification introduced by modern science. (148)

I take this point as an invitation to explore how data feature in life-worlds. How do people as embodied beings experience data?

Data are always experienced through a medium (O’Riordan 2017), as also pointed out in the introduction. The medium materializes the data. Today, the medium is typically a digital interface. Also, the form—graphs, tables, spreadsheets, and so on—matters. The social nature of the encounter with data similarly shapes data experiences: With whom do people experience data? At work, in the clinic, or at home, for example? In the course of doing what? I contend that data experiences in healthcare primarily play out in relation to the four types of activity outlined in chapter 3 as data work: *production* (the work going into data production), *analysis* (the work related to data analysis), *instruction* (to govern with, or be governed by, data), and *use* (to access and utilize data products). I have outlined these with examples of potentially important parameters of variance in table 4.1.

The categorization is not exhaustive. Some types overlap. There is, for example, no absolute distinction between analysis and use, as any use will involve an element of interpretation. Accordingly, my examples in this chapter will illustrate overlaps. The table primarily means to illustrate the diversity of data encounters. We should not expect data to awaken similar reactions even in the same person when situations are so diverse. Also, in

Table 4.1

Four types of activity that give rise to data experiences

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Data production	<p>At own will with your own purpose (e.g., doctors trying to systematize their work, a researcher or administrator wanting data to answer a question, or a self-tracking citizen)</p> <p>When asked to make data for others and for purposes defined by others (e.g., a nurse asked to fill in quality data to document performance or activity, or a patient filling in questionnaires)</p> <p>When (consciously or unconsciously) leaving data traces in the course of doing something else that can be used by others (e.g., digital surveillance through monitoring tools)</p>
Data analysis	<p>When initiating your own analysis on your own data (e.g., citizens using self-trackers, or researchers pursuing research questions, or general practitioners [GPs] seeking to identify patients with special needs)</p> <p>When initiating your own analysis using data produced by others (e.g., administrators using clinical data, or epidemiologists using registry data for research)</p> <p>When performing analysis for others on demand (e.g., data analytical teams asked to support particular political projects with “facts”)</p>
Data instruction	<p>When governed by data analyses produced by others (e.g., performance-based management)</p> <p>When working in or designing digital interfaces that use input to modify behavior (e.g., decision-support tools, reminder systems, algorithmic feedback)</p> <p>When granted or denied a privilege based on a data profile (e.g., patients’ access to treatment or experience of prejudice based on diagnostic profile) or designing programs for such decisions</p>
Data use	<p>When accessing data on yourself (e.g., patients logging on to see their health records or use data such as ancestry testing for educational or entertainment purposes)</p> <p>When accessing data on others—legitimately or illegitimately (e.g., health professionals using data produced by other entities as part of care—or to spy on, e.g., an ex-partner)</p> <p>When reading data analyses (e.g., as when policymakers receive input to decision-making, or as when staff, patients and citizens read data products that claim to represent them)</p>

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relation to what might be considered *one* data practice, there might still be *multiple* sites for data experiences, each with their own implications (Moerenhout, Fischer, and Decvisch 2020). Consider again table 1.1 in chapter 1 on the many purposes with data, and it becomes obvious that even though policy discourses talk about for example a diagnostic code in the singular as *a* piece of data, this code is produced in one practice, analyzed in others, and used for governance and remuneration purposes in yet others. The doctor producing the code in a medical record system such as The Health Platform can have an experience which is very different from, for example, the epidemiological researcher analyzing this code on the servers of Statistics Denmark. The “same” data give rise to different data experiences as part of different types of data work, through different interfaces, in different social situations. Just as Merleau-Ponty (2002) pointed to the fundamental situatedness of all experience, any analysis of data politics must accept this basic awareness of the situatedness of data experiences.

The concept of experience remains, of course, anthropocentric. It directs attention toward the human side of the human-technology equation. This is not to say that data experiences are created by humans alone: materiality matters—hence my point about rematerialization. Still, a focus on human engagement is crucial because this inevitably varies even when technology seeks to standardize. There is no end to human variation, as Mills (2000 [1959]) insisted. Data politics unfolds and has implications in the tumult of multiple actors, each one differently situated and variously disposed toward data, and working toward different ends. Awareness of such variances can help raise useful questions about the complexity of data-political effects, while simultaneously providing new methodological angles from which to examine data infrastructures.

Once you acknowledge your own emotional reactions to data, you can begin observing them in others. First, it can make you think: “Why should the others be altogether different from me?” If I myself am not as cool and rational as a computer, for example, I should probably not expect others to use data as if they were computers. Second, the next thought should be: “Some of these other people probably *are* very different from me! They are definitely not as cool as computers, but what do *they* feel? How do *they* react?”

With these theoretical reflections aimed at mobilizing data experiences as an analytical term, I can now turn to the four types of activity: production, analysis, instruction, and use. I begin in each case with my own



methodological experiences and choices, and then relate them to observations in the health services. I use my own engagement with data because it illustrates the challenges associated with the paradox of dematerialization and rematerialization, but also because I think awareness of one's phenomenological experience can be helpful whether done during academic analysis or working with data in healthcare.

#### PRODUCTION: DATA WORK GENERATES EMOTIONS

It gradually dawned on me that it would be useful to theorize data experiences as I acknowledged (I should perhaps say admitted to myself) that I was having emotional reactions to my own data production. These reactions were not particularly flattering. I sometimes experienced a form of exhaustion. One day in October 2017, I added a reflective note about my own data production in my field notes:

I've been out of office a few days, and opening my email it is as if I am drowning. I feel dizzy. I'm flooded by data. I am now fully dependent on digital tools to keep track of the constant stream of news, reports, papers, and press releases. These sources of information probably sometimes become research data partly as a consequence of their digital format and availability through the technological infrastructures I'm embedded in. (. . .) Thanks to my phone, this flow of data hits me constantly and everywhere—when queuing for an airplane or in the [coffee] break at a conference. I transfer links to emails and send them to myself to have them waiting in my inbox when I am back in office. I get too many data and have to make them searchable with keywords. I then transform them into an archive, just like other data sets that need rinsing and preparation. Constantly dreading to lose track or forget something. But I can't help asking: Why does it exhaust me in this way?

What I am admitting to myself here is not just a lack of control and direction. I am admitting to a set of emotions. I had begun wondering why my documentary data practices *felt* so different from my memory of the joyous task of writing notes during earlier fieldwork in Tanzania and Sweden. When doing fieldwork in those places, I used to fill books with handwritten notes and later index them. The very act of writing gave a sense of orientation, as if I gradually mastered the complexity in the course of narrating my experiences. Subconscious omissions probably helped me select among memories and add a sense of clarity, but if that was the case, then the comforting sense of understanding overrode my doubts.

People use narratives to orient themselves (Frank 2012). In the field note, I describe a data production that has become disentangled from analysis. It might be why it was disorienting and exhausting. The note also reveals another source of exhaustion: the technological mediation of my notetaking. Today, it is always on a computer, if not at the time of the initial notetaking, then later (see also Gehl [2019] on the emotional engagement with digital tools). Digital pervasiveness also means that data are potentially everywhere and can be anything (although anything already in a digital format has a greater chance of making it into data archives, as I write in the note with a hint of bad conscience). The Internet has changed my research practices (Meyer and Schroeder 2015). My notes have begun to overflow with hyperlinks and pictures. The notetaking is easier with links. Ease overrides the sense of analytical reward. Digitalization does change “memory practices” (Bowker 2005), but it does so through our emotional reactions—joy, shame, ease, exhaustion—as much as anything else.

If emotional aspects of my data production inform my research choices, why would they not inform organizational and clinical actions? Of course, people in the health services also feel joy, shame, ease, and exhaustion. They do not, however, necessarily react in similar ways to the same tasks. Today, I have come to think that my lurking sense of shame partly reflects an awareness that by admitting to a lack of digital thrill, I have relegated myself to a group of people with limited standing in a world dominated by data promises. It is embarrassing even to talk about handwritten notes to young people who can barely write properly by hand anymore. You feel like the dinosaur who forgot to die.

But my point here is not to defend myself. I wish instead to argue the relevance of acknowledging how emotional reactions to data production shape what we produce, as well as which lives we live in data-intensive organizations. Once you dare to admit your own emotions related to data work (including the not-so-favorable emotions proving that you are not as systematic as a computer or as thrilled about digital interfaces as data promises suggest you ought to be), you begin to see the emotional reactions of others everywhere. Emotions shape what we do, not as some form of primary state of affect (Martin 2013), but as elements of the social texture of being human (Hochschild 1979). Of course—and inevitably—they are important for data politics.

The complaints among health professionals about “meaningless work,” as discussed in chapter 3, are emotional reactions. When clinicians complain

about data production as meaningless work, it might very well be related to the shift from producing narratives (the old means of record-keeping) to producing scattered pieces of information (data entries, smart texts, or codes in response to pop-up windows) (Parton 2008). This type of data work no longer gives the gratifying sense of orientation that narratives do—something I had also lost as I shifted from making handwritten notes to digital recording of links, reports, pictures, and press releases.

Once I had begun thinking analytically about my own data experiences, I was able to notice how clinicians seemed to have a range of reactions. As I pointed out in chapter 3, most clinicians dislike data work without clear clinical relevance. However, their responses to “meaningless” data production come in a range of emotional registers. While some feel ridiculed, others talk about being drained of energy, and still others do not really mind. A nurse, for example, spoke endlessly—while treating me as a patient—about the “ludicrous” Epic system, The Health Platform, “It makes no sense, of course,” and then surprisingly she added: “But actually I don’t mind it that much. It’s kinda like having a break, just filling in stupid numbers.” Apparently, it is possible to experience data work as “a break” even while finding them “ludicrous” at an analytical level. Yet others seem to experience an actual thrill of excitement when confronted with a new digital interface.

Excitement appears not to be as common in relation to data production as it is with data work relating to analysis. I noticed how the face of a psychologist at a seminar lit up when telling me how she would spend hours after work exploring what the Epic system could do. Although she had not yet found anything of particular clinical applicability, she found the “opportunities” fascinating. For her, the system was like a puzzle, inviting curiosity. I have also noticed such enthusiasm with new software among my colleagues. They have sparkling eyes and move their heads forward, looking at the screen, in ways that tell me that they react in emotionally more compelling ways to new data interfaces than I, the dinosaur, tend to do.

Acknowledgment of emotional reactions to data production can also add to the understanding of the implications of dissolving referentiality presented in the previous chapter. Those clinicians where the imposition of data work potentially undermines their professional motivation have to find pride in their work, as well as motivation, in new ways. Pride in producing good data is one such strategy. Lars may serve as an example. I interviewed Lars, an anesthetic nurse, a couple of times. He explained how

he personally had come to like some of the features of The Health Platform because he could do his documentation while the patient was anesthetized. Thereby, his data production did not compromise patient safety, he explained, but he obtained significantly better data:

The product that I deliver is better. The way I anesthetize the patient has not changed. It is no better and no worse. But I can document it better. The quality of the document I hand over afterwards has improved.

What he refers to here as the “product” of his work is the data he produces, not the treatment of the patient.

In the national quality organization, where I conducted a number of interviews, the data analysts similarly spoke about “good data” as having value independent of the actual use. Taking pride in good data is an obvious outcome of an organizational culture that distributes praise and blame based on that data. To find pride in data with limited clinical value is a coping mechanism as well as an effect: it helps to reenchant otherwise meaningless data work, though the patient fares “no better and no worse.” My point is that data work generates and operates through such emotions. Data failures can give rise to shame; data confidence can inspire pride. Emotions therefore run through not just data production, but also the other three types of data work: analysis, instruction, and use.

The field note mentioned previously suggests that there is reason to question whether I chose the data or they chose me. Of course, serendipity has always characterized ethnographic methods, but I have no way of understanding the algorithmic forms of selection that shape what I encounter. Of course, I have kept doing what I can. I sign up for press releases and listservs, I follow relevant lobbying organizations, and I do systematic searches on selected topics such as The Health Platform.<sup>2</sup> A lot of it is fun. Production without analysis, however, is not that stimulating for me. I cannot, like the nurse above, consider it “a break.” My sense of exhaustion might reflect how my data production had become increasingly disconnected from analysis. The informational overload makes the thought of subsequent analysis appear overwhelming. If digital infrastructures were part of creating the information overload, it is striking how this overload in turn inspires the use of digital tools to make sense of the “infoglut” (Andrejevic 2013). Thinking becomes a cyborg act. I am well aware that the feeling of information overload is not new. As historian Ann Blair (2010) remarks:

We describe ourselves as living in an information age as if this were something completely new. In fact, many of our current ways of thinking about and handling information descend from patterns of thought and practices that extend back for centuries. (1)

Blair points out that even Immanuel Kant complained about exhaustion in his attempt to keep up to date. Still, the ongoing datafication of our documentary practices sustains the feeling of disorientation. Disconnected, scattered pieces of information, kept in databases that are to be analyzed later, imply postponement: the pile in front of you keeps growing, and it does not yet make sense. Postponement is at the heart of data politics, as I argued in chapter 1, but people relate to it in different emotional registers.

#### ANALYSIS: PEOPLE LEARN FROM PEOPLE, NOT JUST DATA

I have just described how the speed of communication and overload of information can provoke feelings of inadequacy. Yet observing close colleagues, I see how they can appear empowered and invigorated by the very same elements. For example, during a workshop where we discussed software that analyzed texts by counting “positive” or “negative” expressions in enormous digital data sets, some participants delighted in the ease and sense of quantitative certainty. I focused on algorithmic obfuscation: not knowing what the software does, how it deals with irony, and other such aspects. Conversely, I can observe the sense of unease when quantitatively trained colleagues or students feel uncertain about their own analytical choices when involved in qualitative analysis. I am well aware that some would argue that the workings of the human mind are no less obscure than algorithms (Kahneman and Klein 2009). We are, at least on the surface, remarkably different in this respect as well: some people tend to trust computers more than the minds of humans, and others trust human judgments more than digital calculations.

The point is that the data experiences of analysis are not epistemological alone. They are embodied. Embodiment is social. It emerges through interaction with other people. How we feel affects our analytical decisions and which analytical products we trust. Once we acknowledge the inevitable human variations, we can avoid seeing the choices of others through a deficit model compared to our own,<sup>3</sup> and instead rethink our reasons for

trusting an analysis, case by case. This goes for research as well as organizational decisions and clinical work. If data experiences shape the dimensions of reality that researchers decide to include in their analysis, why should policymakers, administrators, and clinicians be any different?

Even those people who prefer calculations to human judgments still have to make judgments themselves. These judgments are inherently social. Even people who are the most digitally invigorated and enthusiastic also orient themselves toward fellow humans. Chapter 3 described the rising authority of data (“we build arguments with data”). As Charles Taylor (1994) avows, people want the recognition of other people. Therefore, people feel attracted to the types of analysis that are acknowledged by people around them. When I have participated in meetings, I have begun noticing that they are full of references to relations, experiences, and personal impressions. Which *data* are allowed to count—that is, to be considered significant—depend on *whose* opinions and experiences likewise count in that given meeting. Data as such rarely dictate decisions among people. The politics of recognition guides data selection in any given organization. In a healthcare system permeated by data promises, quantitative data tend to provide speakers with more recognition and authority. It is to gain recognition from others that clinicians “build arguments with data,” not out of mere epistemic curiosity.

We are all influenced by the thoughts of others, but we each react very differently to the various *forms* in which we encounter them. For me, interviewing is engaging in ways textual analysis is not. Others feel exactly the opposite (Žižek 2020). In participant observation, we take clues from people in an embodied way. Some researchers feel comfortable, even enlivened, by that form of intersubjectivity, while others feel uncomfortable or exhausted. Similarly, classic studies of organizational managers showed how some prefer taking clues for action from people, and others from written sources, when forming opinions (Stewart 1967).

To provide an example of how interviews work on me with more strength than documents, I return to Mona (discussed in chapter 3), the experienced data analyst who had worked with the integration of data at the regional level for years. I was struggling to understand why quality databases previously kept by the regional level had to begin sending backup files to the Danish Health Data Authority. According to the written documents, the board was not supposed to use the data as such, so why did they have to be pooled? In the course of an interview, Mona then explained:

Yes. Now they want to pool the data, and then you've suddenly got, so to say, a *hell of a lot of* information about all citizens in Denmark. There might be ten [citizens] who are not registered somewhere, but then they must have been born abroad, really. . . . Then combining all these data sources we can actually have sort of a constant state-of-health register, which provides us with a real-time picture of the state of health in the population: How many smoke, what do people weigh, how much do they exercise? (her emphasis)

There was something about the sparkle in her eyes and her gesticulating hands as she conveyed her sense of pervasive overview that worked on me very differently from the various reports making similar claims about data power. She was bolder. It was obvious that she believed in the power of data; it was not just a strategic discourse to her. What is more, Mona went behind the polished statements in the reports. She conveyed her doubts. It turned out that Mona was not 100 percent comfortable with the compilation of data at the state level. Referencing George Orwell's novel *Nineteen Eighty-Four*, she says it makes her think of "Big Brother." She then goes on to refer to this "Brother" as an unspecified plural "they": "The reason I am a tiny bit worried is that they can't say why they want all these data. They just want them (. . .) I guess it provokes some form of anxiety; that they will be abused."

Although Mona is proud of what she thinks data can do, the conversation allows her to communicate doubts of a different order. Again, bodies read bodies in ways that affect them personally. I feel worried, not because of any specific information provided, but because *Mona* is worried. The change in her mood, the way she was trying out the thought, affect me in ways that documents cannot. I had previously interviewed Teis, who also used the image of Big Brother, as he said:

Really, George Orwell, *Nineteen Eighty-Four*, he only touched the surface of what we store on citizens today. If Denmark was to become a dictatorship—it's difficult to imagine, but if—it would be GDR [the former East Germany] on speed. We could keep everything under relentless surveillance and constantly know everything about the citizens. It really could be abused, if anybody wanted to.

The difference between interviewing him and interviewing Mona is that Teis expressed no worry. It was Mona's lack of comfort with data pooling that made me bolder. After several such encounters, I dared questioning the logics of data accumulation more openly. If emotional clues from people affect me, why would others be altogether different?

Knowing is socially embedded all the way through (Mauss 2007; Hastrup 1995). Not only are our thought styles shaped by communities of practice,

as observed already by Fleck (1979), but we also glean much more than information from the people we work with. When we have repeated meetings with people, for example, we learn to respect (or sometimes disrespect) the opinion of others. They become a filter through which we take in new information. We orient ourselves through the values and beliefs of the people we respect. Sometimes emotions probably shape what count as facts rather than the other way around (Durnová 2019), even among anthropologists (Horowitz, Yaworsky, and Kickham 2019).

The ability to orient myself through others has been a very concrete experience for me in the project that led to this book. As described in the preface, I have had the privilege of working closely with a group of excellent scholars. They have conducted fieldwork in various clinical environments, and it is by collaborating with them that I have been able to engage everyday practices across many clinical specialties. I could never have gained intimate familiarity with so many clinical settings on my own. Working with other people entails a methodology of traveling experiences, as it were, where the experiences and interests of others become part of my thinking (see also Korsby and Stavrianakis 2021). I have often found myself pondering, “What would this-or-that colleague say?” when considering an idea. Relations direct curiosities and shape judgment.

Continued collaborations are therefore much more than data exchanges: they shape which data to look for and how to make sense of them. When we reflect on our own data experiences in this way, we can begin to recognize how the people we study also take clues from other people, not just from data. If I learn something about data infrastructures from interacting with Mona—something that I cannot discern from documents—then the people building these infrastructures probably also use multiple forms of impressions when doing their work. They do not just compute information; they learn from other people. In line with this, Jensen (2022) shows in her work on organ transplant coordinators how it often takes social skills and diplomacy to make health professionals produce and use data. What data do depends on the social networks in which they operate.

Finally, the way that people take clues from people, not just from data, relates to the need for context. When discussing organizational questions, we academics do not just throw data at each other: people expect context. If scholars do this when comparing research sites, why do organizational



policy papers today increasingly disregard these classic forms of knowing the organizational context and claim a need for data instead (Pedersen 2019a)?

In organizational matters, people always learn from people, not just data: analyzing is a social act. Clever organizational decision makers know that organizational issues vary according to so many parameters that they need to discuss ideas that were developed or tested in other organizations with local teams before they can assess their feasibility in their own case. Still, data promises are marked by a consistent longing for standardization and transferability. Strategies aim for forms of analysis that can be streamlined, applied to all organizations, and scaled up, and give the same result each time. They aim for predictability. At the heart of predictability lies standardization. In order for data promises to fully materialize, people would have to become more standardized and predictable—that is, more like computers.

#### INSTRUCTION: PEOPLE ARE NOT COMPUTERS

People are not computers—or even like them. It is as embodied beings that humans experience data. Just like it is an embodied experience to produce and analyze data, it is an embodied experience to be governed by data tools. I think all academics feel the yoke of data instruction crunching in on them. We feel the increasing weight of tasks that we are asked to do so the administration can monitor, in particular ways, our academic performance, our teaching, and our financial expenditures. In this regard, academics experience demands akin to those faced by health professionals (Biagioli and Lippman 2020). What may we learn from our own complaints about “meaningless work” when governed through data tools?

I admit to feeling an irrational resentment of having to use a *particular* accounting system for reimbursement of travel expenses. I can hear myself complaining about the time it consumes and how I am certain that it makes traveling more expensive. Actually, I know that these reactions are also a consequence of my dislike of working with the system, not just the potential costs associated with it. My dislike preceded my analysis of the system. Had it been smooth and fun, I might not have bothered to analyze the financial cost. In contrast, consider the delight of a Google search. It is so easy and efficient—at least if you do not bother to read the terms of

agreement policy. The accounting system that I dislike has a counterintuitive interface and yet I have no free choice. I must use it. Counterintuitive computer interfaces eat motivation for breakfast. Conversely, seamless and engaging interfaces like Google and Facebook eat data-security awareness for breakfast. They leave you feeling good, with no urge to analyze their implications.

The use of data governance in academia is about more than bad information and communications technology (ICT) design. It changes priorities. Just like clinicians, academics respond to measurements (Shore and Wright 1999, 2001). A colleague of mine at another university told me that he could see the rush of adrenalin when people looked up their own citation numbers. I have rarely observed other academics looking up such numbers. It is a private practice in my institution. Still, it is obvious that academics respond emotionally to data representations that pertain to themselves. Like the clinicians described in chapter 3, studies show that they also begin gaming the system to get better scores (Power 2020). Wounters (2020) argues that academic gaming is not even really cheating; it means to respond to signals in the system—delivering what you are asked to deliver. I cannot count the number of times that I have been called naive when arguing that we need to think about the *goals* of the university, not just its *measurements* when assessing performance. Gradually, I have come to acknowledge that perceptions of academic performance are now inseparable from measurements of academic performance.

When acknowledging that academics respond to data instruction in embodied and emotional ways, it becomes obvious how data politics in healthcare is full of such data experiences. Clinicians can be proud and happy when reaching a goal, even while questioning its clinical relevance. Administrators *feel* data achievements, they do not just work to achieve them. My notes are full of scribbles about people referring to “green” numbers (goal reached) with satisfaction, and to “red” numbers (suboptimal performance) with distress or shame—even while calling into question both the validity and the relevance of the measurement in question.

How about the data experiences of patients? Patients increasingly receive instruction through more or less automated systems. Automated systems are also used for data collection. As the people creating the system and those summoning the patient to an examination often do not themselves see the

patients, they do not always realize that the data are never used. A physician told me that often patients would be “furious because they fill in all of this and then I never comment on it. But I simply haven’t got the time!” Langstrup (2018) has shown that the people who design these questionnaires are very aware that they need to be used in a clinically relevant manner, but they cannot control how they are distributed and used.

In 2020, for the first time in many years, I had a number of medical appointments for what turned out to be innocent ailments, although they—due to my age, as I was repeatedly told—prompted standard examinations to rule out cancer as the cause. These examinations allowed me to experiment a bit with the role of the patient. Sometimes, for example, I would fill in the questionnaires that popped up automatically on platforms on which I was informed I needed to check in before an appointment. Sometimes I decided not to fill them in. It did not seem to make any difference. I also received an automated instruction to print a questionnaire and bring it along, but when I tried to hand it in, they said they did not want anything on paper. The nurse welcoming me said, “I really don’t know who sends out those letters.” It was something “that came with this Epic system,” I was told. Others asked me to fill in the questionnaire a second time because they could not access my answers in the system, again blaming Epic. It feels slightly odd and rather unsettling to have just filled in a questionnaire and then be told that the data are already “lost” in the system. For another appointment, a nurse called me on the phone, saying I would get a letter in my electronic mailbox that I should not read—she just did not know how to stop it from being sent. It was an automated function in the Epic system. I could not help myself—I read the letter. It began with “This letter contains very important information. You must read it carefully.” The whole episode made me laugh, though it was of course very sad.

As with my distaste for the accounting system that I am obliged to use at work, I noticed how being obliged to use particular data-gathering tools as a patient affects the experience. When some apps suddenly become very popular on the global market, it is because they are picked up by users wanting to experiment with them. Often they abandon them later (Finkelstein, Haaland, Bilger et al. 2016). The availability of options can make a world of difference for the data experience, but it is rarely taken into account when the health services seek to find, for example, the best monitoring tool for all

patients associated with a given ward or clinical specialty: healthcare systems tend to depend on one size fitting all. The chosen tool, however, will give rise to different experiences for different patients. No size is best for *all*.

Most people, whether working in academia or in the health services, like rewards and dislike punishments. In that sense, they are like computers—they are just not as easily standardized. People evade, omit, and transgress systems because they—as individuals—are working toward slightly different ends. They remain unpredictable. Furthermore, for most organizational decisions, data are not used in a truly automated way, but selectively. The selective use of evidence (discussed in chapter 1) makes more sense when we accept that people are not computers. The cases that caused the most distress in the data analysts that I have interviewed were those where the analysts had to deliver data to legitimize planned redundancies, cutbacks, and firings of unpopular employees: these were decisions made by humans on grounds that were anything but data-driven; data were just the fig leaf covering up the real reason behind the act. Humans react differently from computers when confronted with such decisions. Decisions like these matter to humans on an emotional level on which computers, as far as we know, do not operate.

#### USE: DATA EXPERIENCES INFORM THE PATH OF ACTION

How do people, as embodied beings, use data products? How does a person *experience* seeing a graph, a heat map, a list of red-yellow-green statuses? How do they experience an interview quote or clinical narrative? Through which medium, and in whose company, do they engage these data representations? To appreciate this dimension, I again have had to reflect on my own methodology. How do *I* engage with data representations, and how do *my* methodological choices reflect what I consider good data? Which type of data user am I? Only then have I been able to look for differences in others. Users engage technological products in a range of different ways (Oudshoorn and Pinch 2003; Hyysalo, Jensen, and Oudshoorn 2016), and data technologies are no exception.

As embodied beings, we are all at the mercy of our own embodied being-in-the-world. It took some time before I realized that the discussion of “what data mean” (as presented in the introduction) involved this more phenomenological dimension too: what do we, as users of data, even recognize as data? In my initial anthropological training, I was always told

that “everything is data.” This was—of course—a lie (Brinkmann 2014). The constant encouragement to see everything as data was intended to persuade us, as students, to pay attention to that which other disciplines often neglect. Being *present* in the course of everyday life is supposed to allow anthropologists to go “beyond the words” (Wikan 1992). Instead of numerical clarity, the point is to create dense and thick descriptions. In that training, the word “data” clearly meant something very different from the general use of the term in the health services that I now study. Ethnographic data do not come in computational formats only.

Ethnographic presence gives access to types of knowledge that data science does not, exactly because it draws on bodily experiences and the ability to build a rapport with people. It is through this rapport—as when Mona conveys what she can hardly articulate—that interesting interview data are produced. The willingness to acknowledge the messy and intangible, the tacit (Polanyi 1966) and that which is difficult to record and document, also has proved itself useful when working with datafication processes, as demonstrated by Sally Merry Engle, Vicanne Adams, Cristal Biruk, and others (Hunt, Bell, Baker, and Howard 2017; Biruk 2018; Adams 2016a; Hutchinson, Nayiga, Nabirye et al. 2018; Merry 2016; Sullivan 2017). Not everything makes it to the field notes, however, and Jacques Derrida’s point that the archive is characterized not only by what it contains but also by what it omits has enduring relevance for qualitative researchers (Derrida 1995). The anthropological ambition creates its own silences and omissions. The credo of ethnographic presence downplays the value of stories in television and in newspapers, such as the media reports on a man without a CPR number (chapter 2) and the public conflict about Morten Hedegaard (discussed in chapter 3). Still, I maintain that data politics is also what is happening in this type of public contestation. Although not ethnographically thick, it is “thick data” in a different sense when Hedegaard’s resignation or a man without a CPR number attract massive attention. Journalistic framings say something about what is considered newsworthy in a given context, even though the individual story behind the news will have other facets. Any form of academic training establishes its own hierarchy of data, and in some cases it is important to rethink what might be data for the topic at hand rather than limiting yourself to what can be studied with what is usually considered good data in everyday organizational practice, as well as in research.

If I sometimes select data according to tacit disciplinary habits and fear negative reactions when I do not follow conventions, why should other people—researchers, administrators, or clinicians—be any different? When data users select which data to consider, I have come to think that they often do so partly in light of how they themselves experience data. Just as interviews invigorate me but are deeply uncomfortable for others, I have begun noticing the relief that colleagues express when finally presented with a graph or table after a discussion of quotes from interviews. Just as we approach the analytical tools with different dispositions (as in the case of algorithmic software counting negative and positive words that I have already mentioned), we consume data representations within various emotional registers. For some, a graph is alienating, but for others, it is a comforting reduction of complexity. Healthcare organizations employ people who feel differently about different data types and data representations. Each person gets a different energy from interacting with data representations, and each makes different selections and omissions. It might be dangerous, however, to ignore the competences of people in areas such as clinical care just because they are not particularly good with digital tools.

Without appreciating the variation in how patients engage data and data presentations, medical professionals cannot communicate treatment plans and monitoring goals effectively. Some patients find graphs comforting, but their interest in being comforted can also make them pay attention to only those data that provide such gratification (Weiner, Will, Henwood, and Williams 2020). Selective attention and registration is similar to gaming the system, but with the aim of achieving a particular data experience. Some patients feel vexed when realizing that they have moved without their pedometer and lost the data (Wienroth, Thomsen, and Høstgaard 2020). Emotional reactions to data practices make us into different types of data users. They shape the paths taken in research, organizational practice, and everyday life.

#### PUTTING DATA EXPERIENCES TO WORK: THE CASE FOR SELF-EXPERIMENTATION

What began at the optician's as an ethnomethodological moment, by sheer coincidence, has for me become a stable ingredient in my methodological toolbox. As human beings, we have to use ourselves to grasp the phenomenological experience of data. Now I take this point a step further and argue the value of self-experimentation by design, not just by accident or

necessity. Self-experimentation involves working reflexively with yourself as a sensing tool. I have illustrated each of the four types of encounters with data with reflections on my own methods. Reflexivity may sound like something an individual builds in an armchair in solitude. It is not. It emerges through social practices. By acting in the world and getting reactions, you learn from those reactions. To do so, you do not necessarily have to be an embarrassment to your fellow human beings—or an obtrusive patient experimenting with questionnaire compliance. You can self-experiment in less intrusive ways. I will provide a few examples (and let readers judge the level of embarrassment I should feel).

When reading a paper stating that back in 2008 that it would take on average 201 hours a year to read the terms of agreement needed to access the number of digital services a typical citizen uses (McDonald and Cranor 2008), I decided to try it out myself. For a year, I would read all new terms of agreement before clicking “Accept,” and I would on each occasion record the time it took. I wanted to see how it would be to actually do what most agreements write at the top of each document: “Read these terms carefully.” Admittedly, I could not carry this task through. First, I gave up recording the time. Measuring time was in itself time consuming . . . and—for me—it was too boring. Boredom is a feeling that (unfortunately) influences many choices of data production, as noted previously. Second, sometimes it was just too grueling to figure out whether I had followed all the links in the agreement. I simply could not figure out what the terms of agreement even were. Third, some weeks were too busy, and I had to employ an assistant to read the agreements (typically between 5,000 and 9,000 words) and send me a short summary so that I could at least categorize the type of agreement.

Nevertheless, by reading several hundreds of terms of agreements, I did learn a lot about the conditions of capturing data from citizens (Larsson 2017). Just as important, I learned a lot from experiencing the feelings of apathy and disempowerment involved in trying to understand what I was agreeing to (Obar 2017). Sometimes I had to click “Accept” no matter how unreasonable the agreements were because of relations of power. For example, I ended up accepting data sourcing in a case where an internationally publisher of high standing had made an online portal mandatory for authors to sign contracts. As I complained about how the conditions for using the portal included offering my data for sale to third parties, it turned out that the contact at the publisher had not himself read the terms of agreement—and could not locate anyone who had. In the course of the

year of enduring this self-experiment, I understood the absurdity of presenting terms of agreement as a contract protecting the rights of users, and at the end of the year, a childish joy—a form of conscious cheating—could erupt when I again was at liberty to click “Agree” without even trying to read the terms. Yet there is no way back to innocent clicking once you have seen enough of the often absurd terms.

Another form of self-experimentation is to throw yourself and your ideas into the arena you study. That is, you can turn your thinking into data representations that you can then observe being processed by others. For me, this has involved engaging in discussions about data politics in Denmark as well as abroad. As part of this engagement, I published a book in Danish about health data designed in a short and popular format to stimulate debate (Hoeyer 2019). It did the trick. I was invited to speak at numerous meetings and conferences, as well as in informal meetings with policymakers who were preparing new initiatives and looking for feedback on the feasibility of the proposed ideas. Some of these events were high-profile ones with leading figures such as the prime minister, cabinet ministers, and key industry representatives. Others were low-key, for the people engaged in the everyday work of maintaining a data-intensive healthcare sector. During these seminars and in the course of conversations with the organizers, I made observations on their reactions: What works on people in these organizations? What do they recognize as data? Audiences became sounding boards for the ideas presented in this book, and informal chatter with organizers and participants generated new data for me. Reactions from people are more than data, though; they have come to shape my concepts and thinking as I searched for a vocabulary that made sense also to them (Marcus 2021). I also saw that even when people claimed to “build arguments with data” and aimed for a “data-driven organization,” I needed to speak to the *emotions* that data work entailed for them—for example, to speak to the pride evoked by careful data analysis and point out how much work it takes to deliver that type of analysis. Speaking to the sense of pride works much better than warning against hype.

In general, I also respond to hearings on new legal proposals and ethical reports. In this way, I take on the role of political actor and not just an observer of data politics (see also Sharp 2019). Working as I do in a medical faculty, several of my colleagues are involved in planning and executing data-intensive initiatives for health sector research. As a “data expert,” I am regularly seconded to committees and advisory panels of various kinds and



attend seminars, inaugurations, and management meetings where I hear colleagues discuss the types of work that I study. Meetings are intriguing, at least methodologically speaking. However, when anthropologists write about meetings, they generally approach meeting participants as “study objects” (Brown, Reed, and Yarrow 2017). I talk about attending meetings because I had to, as one of the participants. I was not doing participant observation; rather, I was an observing participant. Some of the examples given in this chapter come from notes taken during or after these meetings.<sup>4</sup> In the meetings, people informally articulate their fears, their pride, and their longing—sometimes even their shame—relating to data in ways that they would never publish or concede to in an interview. These meetings have confirmed that data are indeed experiential objects that work on people as people work with them. By bringing attention to data experiences, I want to encourage those working with data and infrastructures to begin using *what we know as human beings*—not just what happens to feature in the data sets that our disciplines or organizations make us think of as paths to “real” knowledge.

## PARADOXES OF DATAFICATION

The kind of politics that revolve around data is coproduced with the experiences that people have when engaging with the data. By becoming aware of our bodily data experiences, and of how we engage the simultaneous dematerialization and rematerialization, we stand a better chance of seeing when emotional and embodied reactions matter for others. This awareness is a bridge to understanding data politics, but also to building more inclusive data infrastructures. Human beings differ in infinite ways. The infrastructures in which their lives unfold must provide space for all this variation. Datafication depends on and becomes successful through standardization, but humans are never fully standardized (Büchner 2018). At the heart of this paradox lies a reason for continued curiosity: nobody should expect data tools to do only what they expect of them.

Which type of politics do these paradoxes propagate? Why do the paradoxes persist? If everybody knows that people differ, why would somebody insist on the ultimate power of standardization? This is similar to the paradox of dematerialization and rematerialization: If everybody is an embodied being and every being can work with data only through material interfaces that generate emotional reactions, why would anybody insist on thinking of data in a purely dematerialized way? Perhaps the reason is that many things

are easier with selective knowing, in the short run at least. A policy focus on *one* side of the story, dematerialization or standardization, redistributes and focuses epistemic authority. When Negroponte (1995) suggested that bits would take over from atoms (as mentioned in the introduction), he was writing on a computer made of atoms. He did not produce atoms, but he was a master of bits, and his narrative form privileged his own kingdom.

Loukissas (2019) suggests that Negroponte's dogma about dematerialization is facilitative for governance at a distance in a more general sense. If we relate it to the organizations described in chapter 3, it means that those who use data for instruction are not confronted with how other people—as atoms—are affected by their decisions. Some of these effects are planned, others unexpected. The two paradoxes allow people to use standards and see the inevitable variation as "human error"; coexisting narratives allow them to exert power as information and to ignore the diverse material effects. Those making the decisions can focus on the aspects they wish to govern and ignore the others, whether they relate to race, age, sexuality, or anything else reflecting the endless variation in human lives. Through awareness of the paradoxes, conversely, the effect of data on everyday living becomes thinkable—and thereby actionable—in new ways.

I have written this chapter to create an awareness of data experiences as being the embodied way in which every human must deal with data. My interest in data experiences began with the challenges associated with the second paradox that has been weaving through this chapter: data dematerialize and rematerialize interactions. I was studying ephemeral data infrastructures that I could not localize. My problems reflected the multiplicity of data: data were many things and in many places at the same time, as when a CPR number could at once be at the optician's, in an insurance agency, and in a bank—and simultaneously be used for very different things, such as record keeping, marketing, calculation of remuneration, and money transfers. While data dematerialize interactions and create connections between people who do not themselves know how they connect (or even that they are connected), data also rematerialize. They appear on computer screens—through material interfaces. Through such interfaces, people experience shame, joy, and pride—sometimes provoked by clumsy questions. Data have material effects. These wider and socially engrained experiences are *part of* the infrastructure, and when acknowledged as such, they are options for understanding important dimensions of what data do.

The points I have made here can be summarized as five lessons about data experiences: (1) data work generates emotions; (2) people learn from people, not just data; (3) people are not computers; (4) data experiences inform actions; and (5) the primary tool for understanding data experiences is self-experimentation. The fifth lesson suggests that both researchers and organizational actors should reflect on their own experiences to understand what data tools do in practice. Self-experimentation is the bridge to the other four. In our own reflections, there is no point in limiting what counts as data to that which can be processed by a computer. It is better to let computers do what they do well, and let human understanding draw on as broad a set of experiences as possible. We are our own primary research instruments. When we reflect upon our own reactions, without prejudice about what counts as good data, our understanding expands. Often, we become better at seeing even those around us who are clearly very different from us.

Awareness of data experiences also provides new avenues for exploring other abstract phenomena known only through data, such as population politics (Grommé and Ruppert 2020), climate change (Edwards 2010), and the COVID-19 pandemic (Caduff 2020). These phenomena all depend on data to emerge as political entities. Data also make them subject to experience. It is through experiential appropriation—*data experiences*—that datafied entities become subject to action. To know how and why some people react to datafied phenomena (such as a pandemic threat) as they do, it is unwise to ignore how they experience data and representations of data such as graphs, tables, and heat maps. When scholarly work and policy papers refer to data as only epistemic or governmental objects—as carriers of information with purpose rather than objects for emotional and bodily engagement—this reduces disagreements about these topics to questions of misunderstandings or “fake news.” Contemporary political struggles, therefore, might find new paths out of the deadlock of “truth wars” if scholars are willing to explore the experiences through which disagreements emerge.

Computers are good at computing. Humans, however, possess a reflective capacity for thinking about *how* they know something. This capacity is central for making judgments. Many policymakers—and some computer scientists—nevertheless seem to wish that humans would be more like computers—that they would simply *compute*. Wisdom does not arise from data without judgment; however, and therefore, chapter 5 explores what it takes to exert judgment and use data *wisely*.



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# Data Paradoxes

## The Politics of Intensified Data Sourcing in Contemporary Healthcare

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