

CONCLUSION: DATA PARADOXES

What are the drivers for, and the implications of, intensified data sourcing? I have been pondering this question for years now, and rather than clear-cut answers, my pursuit of answers has led me to a set of paradoxes. Every time I have identified one driver and one implication, I have realized that intensified data sourcing also involves very diverse—sometimes almost completely opposite—drivers, as well as very different implications for other people elsewhere, or the same people at a later stage or connected to a different agenda. I therefore believe that instead of hoping for simple answers—for example, taking the form of predictions about what intensified data sourcing can be expected to do everywhere and anytime—practitioners and scholars need to remain curious about what is at stake in any local situation. For many anthropologists and science and technology studies (STS) scholars, this attention to locality is already on the menu. The key question is how an improved understanding of the complex challenges of intensified data sourcing also can inform practical solutions and facilitate better future uses of data. I believe that awareness of paradoxes can destabilize premature conclusions and nudge both scholars and practitioners to contemplate additional dimensions of a problem. Paradoxes are complicated, though, because they suggest complexity. Complexity does not easily guide actions. How can we train not just social scientists, but also data scientists, technology developers, administrators, and policymakers to care about local specificities? How can insights from anthropology, STS, and critical data studies help practitioners and scholars from other fields to think about solutions in new ways?

To avoid a deadlock of complexity, I will make two moves. After summarizing my argument about the paradoxical drivers for and implications of intensified data sourcing, I first suggest a new metaphor with which to think about data. Some might say that it is an analogy rather than a metaphor, but I leave such issues to philosophers. Instead of the common value-oriented metaphors of oil and gold, I propose to think of data as drugs. My intention is to stimulate curiosity and encourage better questions with which to explore local implications. My second move is to suggest some alternatives to the dominant framing of the ethics of intensified data sourcing. With a different normative framework, I hope to inspire reflections on how to regulate intensified data sourcing in a balanced manner aimed at the common good. Before I outline any alternatives, however, I summarize my analysis.

WHEN DATA PROMISES HIT THE GROUND: THE STORY IN BRIEF

Contemporary healthcare in high-income countries is becoming increasingly data intensive. A wide range of different stakeholders want more data, of better quality, on more people, and they want to use them for more purposes. Consultants, information technology specialists, administrators, and policymakers happily articulate what I have called “data promises.” In reports, strategy papers, and policy documents, at conferences and during high-profile meetings and workshops, these proponents of data intensification suggest an imminent future where doctors are replaced by statisticians and robots and healthcare governance becomes data-driven through processes that simultaneously ensure economic growth. The result is said to be disruption of healthcare as we know it. As an echo of Facebook’s early motto, “Move fast and break things” (Halting Problem 2017), a new healthcare system is proclaimed to be about to rise like a phoenix from the ashes of the desired blaze.

Despite the high hopes, the bold data promises have a hard time materializing on the ground. An important motivation for me in writing this book has been the plain observation of a series of significant gaps. These are gaps between the promises of disruption and hard-to-change everyday practices; between a sort of data gospel about automation and concrete and often manual data work; and between prophecies of future seamlessness and present-day experiences with hitches and hassles. Of course, data *do* perform important—and expected—tasks in healthcare organizations, all

in line with declared purposes. Data *do* boost research outputs. Data tools *do* deliver more precise diagnostics, treatment, and adequate monitoring of patients. They *do* facilitate increased political and administrative control. Data *do* help to ensure consistent growth rates in the medical industry.

However, investments in data do not always deliver, and sometimes what they do deliver is curiously different from what the promises suggested. Furthermore, most of the new data practices are much more mundane, low-tech, and time-consuming than data promises suggest. Patients and citizens respond to questionnaires. They are asked to rate their ability to self-care on a scale from one to ten. They use monitoring devices and upload results to central databases. Doctors and nurses spend increasing amounts of time looking at data, or trying to find data in the expanding databases. Administrators depend on increasing amounts of data to produce reports on organizational performance, but they sometimes do so while being well aware that these data do not convey an adequate impression of the performance they want to measure. Academic and industrial researchers are obtaining easier access to data, but some new users of data do not know what the data mean. It is all pretty far from the promised magical high-tech dust that was supposed to fall as glitter on the old cumbersome clinical routines.

In place of the total disruption of everyday healthcare practices, we see investments in something slightly duller and more conventional: *digitization* and *information infrastructures*. In place of disruption, there is infrastructural integration. At first glance, infrastructural integration speaks to old dreams of a “world brain” of all available information (see chapter 5). However, after years of data integration, the predominant experience in Denmark seems to be that no system can capture “all data on everything” (see chapter 3). Nor is it possible to reach agreement on what data mean, who should use them, and for what purposes. With the integration of multiple sources of data come not only more information, but also a haze of data, or what Andrejevic (2013) calls “infoglut.” Data integration is never complete, and data are never transparent. The vision of completeness as a step toward a transparent “world brain” of all available information is what Jasanoff and colleagues call a “sociotechnical imaginary” (Jasanoff and Kim 2013; Hurlbut, Jasanoff, and Saha 2020). It works through the ambitions it installs more than the results it delivers.

Though infrastructural changes sound duller than total disruption they are very important. Intensified data sourcing means that data are now

serving research, clinical, governmental, and industrial purposes. This multiplication of purposes is an important transformation. The four purposes overlap (one purpose can become a means for another), and the same actors can be dedicated to several purposes, or even all four of them. I have grouped them in this way to illustrate how various stakeholders want to use data to pursue at least four goods: knowledge, health, governance, and wealth. Each type of good has a less benevolent counterpart. Instead of knowledge, data can be used to create a haze that generates unnecessary doubt or help researchers achieve bibliometric targets without delivering insights. Instead of health, data practices can make clinicians pursue patient satisfaction or other performance measurements. Instead of good governance, data can be used for surveillance and control. Instead of wealth, data may serve plain greed and the unrestrained accumulation of capital. My main point, however, is that even when we accept just the benevolent intentions, we have to acknowledge that the four purposes do not always align.

How are we to understand the friction between these purposes? Cutting across all chapters, I have pointed to the *ontological multiplicity* of data as a key feature of intensified data sourcing. I am well aware that ontological multiplicity is a somewhat convoluted expression, and yet I have found it necessary to use it to reorient the otherwise epistemological problematization of data. My point is that data do not just *mean* several things; they *are* several things, or rather they *do* several things simultaneously. Health data might be data on a patient's disease at the same time that they are data on the treating physician, the hospital, and the laboratory that delivered a test. Data can affect each of these arenas differently, depending on who uses them for what. To accept ontological multiplicity involves investigating data, not just for what they signify, but for the diverse effects they may have in several arenas at the same time, or how effects can shift for the same actors over time. Because intensified data sourcing implies that data serve an increasing number of purposes, they become like cogs operating in several machines at once (to repeat the image from chapter 5). The machines are producing different things, but they depend on the same parts. Such friction can make machines collapse.

I have described a shift from curated transfers of information to automated pooling. This shift accelerates the speed of all the motors in which data operate. In the period of curated transfers, where selected pieces of clinical information went into central registries, there was limited feedback

when data were reused for a new purpose. Researchers accessing data through Statistics Denmark did not report when they found an error in clinical reporting because they were not allowed to disturb a different system. As the various systems become increasingly interconnected, disturbances begin to proliferate. Some of these disturbances are beneficial for patient treatments. Patients can notify clinicians when they discover inaccurate reporting of symptoms; people working with quality controls can ensure higher degrees of consistency in treatment; and doctors can correct their own prescription patterns through automated feedback comparing them to others—to mention just a few of the examples from the preceding chapters.

Other disturbances, however, risk undermining the clinical function of patient data. When clinicians complain about drowning in meaningless data work, that is an important red flag indicating possibly perilous disturbances. When researching physicians seek to boost their research by using their position in reference groups for quality databases to increase everyday clinical demands of documentation and have these demands integrated into electronic medical record systems, then research aims are taking precedence over clinical aims. When politicians and administrators govern through forms of data-work-of-instruction that make clinicians overrule their own best judgment to comply with standardized demands, that is no longer *good* governance. It puts clinical goals at risk. Similarly, the increased emphasis on using data as vehicles of economic growth also risks jeopardizing the public legitimacy and stability of the integrated data infrastructures (Skovgaard, Wadmann, and Hoeyer 2019; Skovgaard and Hoeyer 2022; Sterckx, Rakic, Cockbain, and Borry 2015; Vezyridis and Timmons 2017, 2021).

Data promises draw on powerful ideas about informatization, but bodies and healthcare organizations are always more than information. The care for suffering bodies is difficult to disrupt. The complexity and multidimensionality of bodies cannot be turned into data. Suffering bodies need care. Furthermore, even data infrastructures are material. The bit economy is full of atoms, to turn Nicholas Negroponte's famous distinction against his own vision (Negroponte 1995). Digital data are not just ephemeral, cloudlike creatures. Danish news media even report cases where health data occasionally need to be transported as atoms, literally driven on trucks to supercomputers, because it would take too long via broadband (Møllerhøj and Engelhardt 2013). The constant appetite for data also has important ecological ramifications: digital data tools depend on mining of rare minerals,

constant replacements of hardware, and an excessive consumption of electricity (Benko 2015; Crawford 2021). The internet is already consuming approximately 9 percent of the world's energy usage (Jensen 2020a). Within a few years, data centers are expected to increase the Danish energy consumption with 22 percent (Maguire and Winthereik 2021). Just as datafication does not eliminate bodily suffering, it does not deliver an escape from the climate catastrophe. It is not an option to live a life as just bits, but no atoms.

In the introduction, I suggested that if people want to see what intensified data sourcing looks like in real life, they should go to Denmark. Indeed, hundreds of delegations from all over the world already do just that. Denmark is a showcase for data infrastructures of the sort that the global data promises now inspire elsewhere: digitized healthcare and highly integrated information infrastructures. It is a country readily embracing what I called “wired medicine” in chapter 2—a term coined to capture the changing nature of healthcare in the Global North. However, in light of what I just wrote about the inability to reach the promised land of the data gospel, it should be clear that foreign policymakers will not get what they hope for by copying the Danish setup. Furthermore, even if they manage to establish similar database opportunities in their own countries, other nations will get something very different. With this book, I have argued that data always affect people's lives through local instantiation of infrastructures. This means that even similar software packages conjoined on comparable digital networks will do different things in different contexts. An information infrastructure is never just software and hardware; it is also a social texture shaped by political, economic, and legal histories. It is, therefore, not possible to do a controlled experiment in Denmark and then scale it up and expect it to have the same results in the United States or Japan.

Nevertheless, there is a lot to learn from studying Danish levels of data integration. The Danish experiences suggest a range of potential implications. For example, despite promises of seamless automation, intensified data sourcing generates new forms of work. I have suggested grouping data work into four types: *production*, *analysis*, *instruction*, and *use*. Data are not free. Besides the expenses related to work, intensified data sourcing depends on infrastructures that are expensive to establish and maintain. The more complex an infrastructure gets, the more repair work it demands. Nevertheless, policy papers often present data as a form of commons out there—available

and free. I therefore believe that my argument about the ongoing transformations being different from the disruption evoked by data promises carries a more general insight that reaches beyond Danish borders.

Infrastructural changes may have profound effects. Academic observers, media, and policymakers have a well-known tendency to simultaneously overestimate technological transformations in the short run (as when expecting a total disruption) and underestimate their long-term implications. Technologies of data are no different. With the early registries and their curated one-way transfers of information to central databases, narratives remained local and in the custody of the clinicians. With the gradual shift toward automated pooling of data, even the narrative part of patient documentation is now “potentialized” for infinite future reuse (Taussig, Hoeyer, and Helmreich 2013; Bowker 2005).

As clinicians no longer control who gets access to what, notions of professional confidentiality may transmute in ways that we cannot imagine yet. Also, data are used in organizational decision making in ways that are destabilizing ideas about knowledge. Much to the regret of clever and experienced data analysts, the increased focus on becoming data-driven has meant that the political and administrative top management have become increasingly content with quick and dirty uses of data. The time and resources needed to make sense of data are lacking. By centralizing data infrastructures and opening them up for multiple and simultaneous forms of (superficial) data reuse, the conditions for politics are thereby changing. Power balances shift. When data serve as handmaidens of decision-makers, intensified data sourcing also affects something even more basic for the human perception of the world: what counts as true. Intensified data sourcing thereby undermines the epistemic authority of data that gave them their appeal and authority in the first place. In *The Postmodern Condition*, Lyotard noted how the computerized database gained authority through a notion of data serving as references to particular aspects of the outside world. Databases were dissolving this reference, Lyotard (1984) argued. According to Poster (1990), the point was that “increasingly meaning is sustained through mechanisms of self-referentiality and the non-linguistic thing, the referent, fades into obscurity” (13). Intensified data sourcing seems to involve an organizational willingness to accept dissolving referentiality.

It may sound abstract, but I am pointing to something very concrete. In systems ruled through data, health professionals and bureaucrats have to

manipulate data. It took more than a century to build the social robustness of claims based on data and to make people trust a data analysis (Oreskes 2019; Daston and Galison 2010; Zuboff 1989). Anthropology and STS have taken issue with this robustness and its implied objectivity. However, now is also the time to express concern about what will happen if trust in data disappears (Poirier 2021). If it becomes an everyday organizational reality that data cannot be trusted, then what steps into the place of trust? What fills the void? These changes might be more profound than what is suggested by terms such as “smart healthcare.”

I do not suggest the resuscitation of blind trust in data. It is not useful to claim objectivity and cover up opinion as facts. I think that greater acknowledgment of the *limits* of data can help preserve all the benefits of intensified data sourcing. The first step is to acknowledge that healthcare must build on several types of knowledge. It is important to talk about tactile skills, action skills, and—perhaps—about *associative thinking* as elements of both clinical and organizational judgment. Similarly, it is important to acknowledge *data experiences*. Data work on people. They work on embodied beings. Humans are poorly understood when viewed simply as faulty computers. They form judgments in other ways. These ways need training (Kahneman, Sibony, and Sunstein 2021). Training depends on strong institutional cultures. To get out of the promissory cloud and back onto the ground, therefore, is also to get back into the body. It is to get back to a serious engagement with how human beings think, work, and thrive. In contemporary healthcare, clinicians and administrators must be able to read and analyze data, but they must also be able to identify the proper space for data among other sources of knowledge. In an even more general sense, the notion of evidence must be broadened. Both clinicians and regulators need to expand the range of knowledge forms that inform their understanding of evidence—and include new big data methodologies, as well as understanding of the social dynamics of data reuse.

As the COVID-19 pandemic struck, bodily engagement with data became a daily experience for most citizens. The pandemic created a data-political moment of unprecedented strength. Politics based on data predictions made the need for careful data analysis more obvious than it might ever have been before. In some ways, the pandemic also became a reason to rethink several of my points, not least the one about the inertia of healthcare. With the sudden lockdowns, rapid reorganization of healthcare suddenly looked possible. In addition, the pandemic challenged the image of

a population comfortable with extreme data integration. Suddenly, some people took to the streets—they challenged test regimes and complained about reuse of data for research. Not only did citizens now question data infrastructures, they also questioned the values informing the data predictions that ruled their lives. Data predictions are analytical products that come in the form of probabilities. Both the proponents and opponents of government politics filled the void of epistemological certainty with a form of moral certitude. This moral certitude precluded a dialogue between what was becoming two sides of a conflict. Data politics thereby seems to involve a particular risk of social bifurcation. Dealing with this risk is likely to prove to be one of the major challenges of our times.

As I have recounted my argument, I have drawn out the most important points from the preceding chapters, but none of these points is without contradictory examples. Throughout the book, therefore, I have told the story through paradoxes. I now recapitulate these paradoxes and my reason for insisting on paradoxical narratives.

PARADOXES: LEARNING TO APPRECIATE OPPOSING STORIES

I believe that paradoxes are useful vehicles for thinking because they inspire us to acknowledge that several transformations can take place simultaneously. Paradoxical narratives stand in contrast to how data discourses usually frame knowledge products. The lure of data promises partly stems from the hope of being able to close a case with a statistical argument. It flattens the dimensions of a problem. It reduces complexity. As Luhmann (1999) has insightfully suggested, most of us have an urge to reduce complexity. Many clinicians have a deep desire for certainty. This is understandable. Clinicians carry the lives of patients in their hands. They want to be sure that they establish the right diagnoses and administer the right treatments. Administrators and politicians also want certainty. They are frustrated about not knowing whether they are prioritizing the right initiatives. When they want to become data-driven, they seek affirmation of their decisions. Paradoxes, in contrast, inspire analysts to be prepared for the unexpected. That can be scary. My hope is that anticipation of paradoxes can make complexity more fun, and in a sense more manageable. If conflicting trends are what to expect, there is a comfort in finding them. The comfort of certitude, however, is not within reach.

I have found paradoxes attractive because for me, they have offered a way of overcoming the division between two positions that have shaped debates about data in the scholarly literature, as well as among the people I have studied: the pro and con positions, the semireligious data gospel, and the unforgiving criticism among data critics. The “Data Wisdom” that I would like to see in healthcare organizations cannot grow in soil fertilized only with hopeful gospel or fearful dread. Paradoxes serve as an invitation to contemplate “both and” rather than “either or.”

In table 7.1, I list the paradoxes I have discussed in the preceding chapters. These paradoxes represent what I believe are the most important implications of intensified data sourcing in healthcare. I have added an extra paradox to the list: *data move too freely, and data never move freely enough*. This final paradox is an addition that represents a fundamental conundrum of all data integration. I described it in chapter 2 as being embedded in the paradox of empowerment/disempowerment when referencing Brown and Duguid’s classic work on “sticky” and “leaky” data (Brown and Duguid 2000). Still, it deserves its own mention in the list because it cuts across all chapters and is endemic to intensified data sourcing: with an increasing

Table 7.1

The paradoxes of intensified data sourcing

Data promises thrive on a claimed need for evidence	... and ...	data needs and initiatives are rarely backed by such evidence.
Data empower citizens	... and ...	data disempower citizens.
Data uncover patient concerns	... and ...	data cover up patient concerns.
Data mean less work	... and ...	data create more work.
Data create meaningless tasks	... and ...	data are used as meaning-making tools.
Data intensification tightens organizational control	... and ...	data intensification facilitates organizational disintegration.
Data become successful through standardization	... and ...	data are never able to standardize human experience.
Data dematerialize interactions	... and ...	data rematerialize interactions.
Data are used to draw invalid conclusions	... and ...	lack of data can be worse.
Data close down and conceal political choices	... and ...	data open up and unsettle political choices.
Data move too freely	... and ...	data never move freely enough.

number of stakeholders, people will not agree on who should use data for what. What appears to some as too-restricted access will be too lax from the perspective of others. This is not a particularly Danish point: it is a consequence of the ontological multiplicity of data used for an increasing range of purposes.

I do not suggest paradoxical thinking as some form of analytical panacea. For me, the figure of the paradox arose as a response to specific challenges associated with data doing different things in different work practices (production, analysis, instruction, and use) aimed at producing different values (knowledge, health, governance and wealth). As I have argued toward the end of each chapter, opposing stories tend to be politically expedient: in the tension between opposing narratives, stakeholders can select the truths that fit their agenda in that moment. The politics of data unfolds in the tension between opposing narratives. Should this paradoxical approach be useful for other social phenomena or practices, it will have to prove it through concrete analysis. It cannot serve as a theoretical dogma replacing empirical engagement.

The various data uses and registers of value have each been carefully theorized by leading scholars in STS, anthropology, sociology, and critical data studies. Paradoxical thinking was for me a way of bringing together the insightful work on how data intensification operates in and affects *research* (Biruk 2018; Prainsack 2017; Leonelli 2016), the *clinic* (Hunt, Bell, Baker, and Howard 2017; Wiener 2000; Wachter 2017), the *administration* of healthcare (Jerak-Zuiderent and Bal 2011; Pollitt, Harrison, Dowswell et al. 2010; Pedersen 2019a; Bonde, Bossen, and Danholt 2018; Hogle 2019), health *politics* (Adams 2016a; Ashmore, Mulkay, and Pinch 1989; Bigo, Isin, and Ruppert 2019; Merry 2016; Murphy 2017) and the commercial actors associated with *industry* (Mcfall 2019; Daemmrigh 2004; Sadowski 2019b; Sharon 2016). It is necessary to conjure these strains of work because the predominant effect of intensified data sourcing is the way in which infrastructural integration makes such otherwise different practices interact.

I am, of course, not the first to write about data paradoxes. Xiao-Li Meng, a statistician, has used the term “data paradox” to describe the counterintuitive fact that exponential growth in data can lower, rather than increase, statistical strength because of increased data velocity and variety and inadequate statistical theorizing (Meng 2018). Media researchers have used the term “big-data paradox” to describe how even with “seeming big data, the

data at the individual level is often extremely limited for most users” (Liu, Morstatter, Tang, and Zafarani 2016: 141). Others refer to “data paradoxes” in a different sense, more akin to “irony” or “sad observation” (Davis 2017; Kaźmierska 2020). This also seems to be the case when the legal scholar Frank Pasquale (2015) talks about how blackboxing of information sources embodies the “paradox of the so-called information age: data is becoming staggering in its breadth and depth, yet often information most important to us is out of our reach, available only to insiders” (191, see also Tanner 2017). I agree with these observations, but this is not how I use the term “paradox” in this book. I think of data paradoxes as instances where *opposing narratives about what data do are both partly true*. With this take on data paradoxes, I wish to prepare the mind for discovering the unexpected, unwarranted, and contradictory effects of new data initiatives.

The embrace of multiplicity and complexity should not make analysts shy away from articulating clear trends. For example, I do think that it is worth noting how healthcare systems marked by intensified data sourcing—in general—come to prioritize research, administration, and commercial interests at the expense of the clinic and patient care. I agree with Kieran Healy (2017), who says that social scientists who only wish to bring nuance to the table risk missing the most important message. Conversely, I am also aware that there are ethnographers who would have wanted to see more detail, more ethnographic presence—more nuance, as it were—in the preceding pages. My analytical ambition has constantly been a synthesis of the drivers for, and the implications of, intensified data sourcing rather than a detailed study of any individual data uses. I wanted to understand what happens when more people want more data and use them for more purposes. I wanted to describe the interplay of policy, practice, and experience. The book was therefore never to be a nuanced ethnography of a particular patient group, clinic, research laboratory, governance office, or country. Paradoxes make it possible to bring together and understand even conflicting local narratives from diverse sites as elements of the same social forces of intensified data sourcing. Rather than dissolving into endless variance (nuance), I think of paradoxical thinking as a way of exploring intensified data sourcing and the shift toward wired medicine in a more comprehensive manner.

Despite the many good reasons for embracing paradoxes, I am aware that they may appear as overly byzantine figures of thought. They do not easily translate into practice. I have therefore thought about how to make

it easier to pose questions that are relevant in local contexts where people work. As stated already, my suggestion is a new metaphor: *data as drugs*.

METAPHORS: OIL, GOLD, OR DRUGS?

Metaphors work as implicit frames of thought (Lakoff and Johnson 1980). I have several times alluded to my discontent with the dominant metaphors for data: “gold” and “oil.” They make the attention revolve around wealth and profit, and thereby tacitly distort how policymakers and administrators prioritize the four types of goods that data are supposed to generate. Sally Wyatt (2022) has criticized the oil and mining metaphors. She points out how they not only lead people to ignore important questions related to how data are made rather than found, but also how people who refer to data as oil do not use the metaphor very well. They ignore, for example, how the oil industry is a source of pollution and a main factor in the climate crisis. They forget the externalities of wealth creation. Kate Crawford (2021) forcefully fleshes out how the data industry mirrors the exploitive mining industry delivering the raw materials for its digital infrastructure, saying that “those who profit from mining do so only because the costs must be sustained by others” (26). It is, as she points out, also how some forms of commercial data extraction tend to work. If used well, the metaphors might do a better job of stimulating reflections. However, as Wyatt argues, unexamined metaphors do not generate genuine thinking; they foreclose it.

I therefore suggest a different metaphor: *drugs*. It can inspire a wider range of questions. In many ways, data already form a part of treatments on par with drugs. Data *are* drugs, as it were. In chapter 2, on data living, I discussed how people like Lone undertake daily data monitoring and sometimes even think that they need a data holiday, just as Kane Race (2009) describes HIV patients taking breaks from their medication. For many chronic patients, a treatment regime without data is no more an option than a life without drugs. By pointing to drugs as a *metaphor* for data, however, I aim at something different. By thinking of data *as* drugs, I suggest using experiences with drugs to pose better questions when examining local data practices.

What does a drug metaphor offer the study of data? Most importantly, we are already accustomed to thinking about drugs as being steeped in paradox. They can be life-saving *and* they cost lives. They are expensive *and* they sometimes help save money. Drugs can do good *and* have bad side

effects. They can heal *and* create addiction. They can be used *and* abused. Each of these paradoxes translates well to how we could think about data practices. Furthermore, a drug metaphor acknowledges that data are not some form of preexisting resource to be drilled out of the ground. Like drugs, data must be produced. Data result from activity, work, investments. A drug metaphor can help us remember that data are never obtained for nothing. The drug metaphor also acknowledges that there are potential benefits: drugs are extremely useful when used correctly. We thereby avoid debates about being for or against data.

When tuning in on the specific implications of a data initiative, the study of drugs has produced insights into mechanisms that can inspire questions that are also relevant when investigating data practices. For instance, it is well known that for drugs, there is a *dose-response curve* in the pharmaceutical effect (where you can get too much or too little of a given drug). Here, the metaphor might make policymakers consider the risks and benefits associated with both too many and too few data—whether in administration or clinical practice—and serve as an antidote to the attitude of “the more the merrier” that shapes many contemporary data initiatives. Drugs are also known to have side effects, and similarly, certain uses of data have unintended and detrimental effects, such as when people gain unauthorized access to patient data or use them for purposes that harm the individual. In an article on confidentiality, Grossman (1977) once made an analogy between data and drugs, noting that “personal data can be poisonous to the patient, depending on who uses it and how it is used” (43).

In relation to drugs, *polypharmacy* is known to involve serious risks of negative drug interactions. Similarly, multiple uses of data also involve risks of negative interactions, and a drug metaphor could inspire reflection on the risk of negative synergy in data initiatives. With drugs, commercial interests sometimes benefit from lacking *diagnostic accuracy* for prescriptions and from inflated off-label prescriptions. Similarly, the companies selling standard data tools sometimes seem to profit from lacking “diagnostic accuracy” with respect to data needs in healthcare organizations. It is a well-known problem with drugs that commercial research focuses on *initiation* rather than *discontinuation* of pharmaceutical treatment (Sismondo 2008; Wadmann 2014b). We can use this insight proactively in relation to data by directing attention and funding toward identifying when data collections cease to work. It ought to be on the agenda for administrators to establish practices

for data discontinuation. Finally, drugs are known for having a placebo effect (Andersen 2011): they make people feel better even when the drug delivers no cure (or, as some would say it, the belief that a drug will bring a cure shapes its effects). Similarly, data proponents often seem unable to question the benefits of their own initiatives. They sometimes even feel an improvement that is so substantial that they ignore critiques from clinicians, as described in chapter 3.

Data tools are not only comparable to pharmaceutical drugs in the sense that they should be prescribed with care (not too many, not too few), studied for what they do in practice (make them subject to careful evaluation), and discontinued when no longer needed. Data practices are also comparable to drugs in a different sense of the word, namely *narcotics*: data can intoxicate and disturb the sense of reality. They can deliver kaleidoscopic visions of organizational reality. They can dissolve the sense of referentiality. Like drugs, data practices can get people addicted. Substance abuse can be dangerous. Data tools are often designed to ensure a form of technological lock-in, where it is difficult, even almost impossible, to shift to a different system. Addiction also comes across as a fear of losing control or overview if a data practice stops.

The drug metaphor and its narcotic associations can also help to shift attention to the more affective dimensions of data that I focused on in chapter 4. A drug metaphor might help stimulate reflections on how data work *feels*. Drugs—pharmaceuticals *and* narcotics—affect your moods. Data are no different. Drugs affect how people view themselves and others (Lane 2007) and can be associated with feelings of pride and shame. Again, data are no different. I found that in hospitals, health professionals sometimes strive to reach arbitrary goals because doing so *feels* better than working with no goal. Data can incite and arouse people—and create excitement and transitory moments of social cohesion. Unfortunately, as is the case with drugs, this can be followed by serious hangovers and withdrawal symptoms. Furthermore, drug experiences are not stable; they develop over time. Why should data experiences be any different? It is worth noting that Wyatt (2018) has warned against the use of the addiction metaphor in relation to digital technology because that construes social problems as individual deviance. She is right. We need an approach to data that performs better than the governance of illicit drugs. Data addictions should not be blamed on individuals. I will return to this point in my discussion of ethics later in this chapter.

A *drug* metaphor—covering both standard pharmaceutical and narcotic connotations—also should inspire consideration of *externalities*, including exploitive global relations of exchange, the risk of pollution, and environmental impact, and it should inspire more work on how to *regulate* intensified data sourcing. For drugs, there are regulatory regimes in place—however faulty they might be—and widespread agreement that there is a need to know something about whether and how drugs work before introducing them in the clinic (Petersen and Tanner 2015; Daemrlich 2004; Faulkner and Kent 2001). Data tools, conversely, are promoted without a similar interest in whether they work and what they do, and they are governed by much more lenient regulatory frameworks than drugs. In 2019, the US Food and Drug Administration (FDA) published an action plan stating that rather than assessing the safety and effect of health apps, they would authorize selected big tech companies to develop them (US Food & Drug Administration 2019; Lievrouw, Marelli, and Van Hoyweghen 2021). Imagine if the pharmaceutical industry were granted the same authority to control its own products. Data tools can rarely be tested in randomized clinical trials (RCTs) as drugs can, but still, it is dangerous to go full speed on a digital transformation aimed at using data tools for treatments without establishing proper regulatory oversight. It is also well known that drugs have more than biological effects and need to be studied from multiple disciplinary perspectives (Van der Geest, Whyte, and Hardon 1996; Whyte, Van der Geest, and Hardon 2003; Greene 2007; Dumit 2012). Similarly, data reach into areas of life that computer scientists rarely have the tools to explore. Different disciplines must collaborate if we are to use data wisely in healthcare.

In short, data are no less important for health services than drugs are. They deserve the same attention. I also hope that the drug metaphor can prompt new types of curiosity aimed at exploring their likely paradoxical implications. Although we are typically told that we should use data to look for *answers*, the most important form of knowledge that any practitioner needs is the ability to pose relevant *questions*. I propose that the drug metaphor will help policymakers and administrators articulate questions that are relevant for their own practices and data initiatives. I have suggested some of them as easy prompts in table 7.2—not to foreclose curiosity, but to sustain it. As Strathern (2007) observes: “We are in great peril if we do not cultivate curiosity in what is around us” (21).

Table 7.2

How a drug metaphor might prompt questions with which to explore local data practices

Metaphorical Observation	Questions with Which to Explore Data
Drugs are expensive to produce.	What are the costs of data, and how are they distributed?
There is a dose-response curve in the drug effects and a need for policies of discontinuation.	When do you collect too many and when too few data—whether in administration or clinical practice—and when it is time for data discontinuation?
Drugs have side-effects.	What are the unintended consequences of data initiatives?
Drugs have placebo effects.	How will we know the effects of data initiatives? Can data prove their own worth?
In drug development, industrial partners have weighty economic interests influencing their advice.	What should count as conflict of interest when companies provide advice on data initiatives?
Drugs have emotional effects and work through embodied experiences.	How do people's data experiences vary, and how do they shape what data do?
Drug use can lead to addiction and abuse and have delusional effects on some people.	When do data tools give rise to lock-in? When do they disturb perception? What counts as abuse?
Drugs need regulation.	How are data tools to be regulated?

ETHICS: THE INTOLERABLE INDIVIDUALIZATION OF RESPONSIBILITY

While this book has focused on the drivers for and implications of intensified data sourcing, my interests have—of course—also been informed by more normative questions. They have simmered beneath each of the chapters: Who is held accountable for data promises? How can the standardization involved in data living make room for human diversity? What is a fair distribution of data work? How can data experiences become recognized as more than a failure of people to behave like computers? What is “Data Wisdom”? I have been pondering these questions because I think that it is important to build and maintain healthcare systems that respond to patient hopes, needs, and concerns, regardless of their backgrounds and resources. However, questions of this type differ in significant ways from the usual framing of ethical issues in data-intensive healthcare.

I needed to first flesh out in detail my argument here before I can go on to explain my dissatisfaction with the dominant framing of ethics and, in particular, the regulatory “solutions” that it has given citizens. To the extent that “ethical concern” serves as the typical counterweight to data promises, there is a need to rethink data ethics. It is therefore with ethics and its relatively meager solutions that I end this conclusion. For some readers, it may seem like a long detour right before the end, but in many ways, it has been the goal all the way through: to recalibrate the way that we think about how to regulate data in healthcare in ways that better balance the forceful data promises.

The ethics of health data have been dominated by discourses about consent, privacy, and data literacy (Sterckx et al. 2015; Dickenson 2013; Dickenson, van Beers, and Sterckx 2018; van Dijk 2020; Piasecki, Walkiewicz-Żarek, Figas-Skrzypulec et al. 2021). The urge to make citizens understand and take control of their own data lives can be found even among scholars who point to the escalating complexity of information infrastructures (Gray, Gerlitz, and Bounegru 2018; Kitchin 2021; Brunton and Nissenbaum 2015). When policymakers address institutional and political concerns, they similarly talk about individual competence and choice. Alternatively, they circumvent ethics and focus on data security.¹ These are all important and relevant issues, but in order to address the concerns associated with intensified data sourcing, the scope of ethics must be broadened.

During the past five years, I have served as “ethics advisor,” as informal discussant on “ethics,” as speaker on “the ethics of data sourcing” at conferences, and as member of all sorts of “ethics committees.” In these forums, I have become dissipated by the intolerable insistence on limiting ethics to questions of individual autonomy and, in consequence, individual responsibility. Again and again, I have heard people who specialize in information technology and work full time with data suggesting that to protect themselves, ordinary citizens should “just” do this or that—typically while pointing to a counterintuitive use of a system designed to make users do exactly the opposite. These extremely well-paid experts, who *build* these evermore complex systems, have the audacity to suggest that *all* citizens should be able to learn to maneuver complex systems as cleverly as they themselves do. It is not going to happen (Obar 2017).

Furthermore, there is no unambiguously prudent way to live with data. Thanks to intensified data sourcing, data are many things at the same time, part of many different projects, and they serve many purposes, most of them

beyond the control of any particular individual. People continue to use expressions such as “my data,” but the very expression “my data” is an oxymoron. Data are always data on somebody or something else too. Nevertheless, data ethics continues to emphasize individual control and responsibility.²

It is important not to forget about individuals. There are good reasons for caring about individual control (Dickenson, van Beers, and Sterckx, et al. 2018). People thrive when they feel recognized and respected as individuals. Patients often have to confide sensitive information to healthcare staff to get help. They care about where this information might end up. As intensified data sourcing affects the conditions of confidentiality and secrecy (Wadmann, Hartlev, and Hoeyer 2022), institutions need to find new ways to respect patient norms and expectations (Nissenbaum 2011). Such norms differ between places and communities (Johansson, Bentzen, Shah et al. 2021). There is a need to rethink how to make individual patients feel recognized and respected. Simmel (1950) noted that “writing is opposed to all secrecy . . . it involves an unlimited, even if only potential, ‘publicity’” (352). As patient information has become digitized, this potentiality is magnified (Manderson, Davis, Colwell, and Ahlin 2015). Data can be repurposed and shared, but they also can be leaked and hacked. Still, patients wish to exert some form of influence over who knows what about them. They continue to expect some form of confidentiality and control.

What have the authorities in Denmark done to ensure such control? What does the common ethical framing offer patients? In Denmark, as in most other countries, patients must provide an informed consent for the treatment of their information as a condition of care.³ They constantly sign informed consent sheets (or, more commonly, click on consent buttons electronically) to verify that healthcare information can be stored. When patients need healthcare, this does not come across as a genuine choice. Rather, they are obliged to do an extra piece of data-work-of-production to legitimize exactly the type of data transfers that most patients want: communication with and between their doctors. Then, once the data enter the databases, they are available for other purposes related to research, governance, and industry. In most cases, data can be used for these purposes without additional consent. Informed consent thereby becomes a pseudo-choice that does not provide patients with any real control.

As a reaction to various citizen complaints about lacking individual control, the authorities have offered citizens various technical solutions over

the years, such as the “privacy marking” option of medical records mentioned in chapter 5 and some opt-out registries. I mentioned in chapter 1 how the Danish parliament in 2014 deleted the largest opt-out registry to date because ‘too many’ had opted out. What type of control do the remaining opt-out registries offer patients? Opting out does not imply deleting any information; it involves being featured in an *extra* registry. In some cases, the opt-out registry can expose patients in new ways. In terms of privacy, patients can be better protected when hidden in large population datasets than when singled out as autonomous decision-makers.

There are opt-out registries for tissue-based research and for withholding genetic information from research, and even some for local record systems. An opt-out registry turns difficult decisions about legitimate reuse of tissue and data into an individualized responsibility, where patients need to know that they can opt out in the first place and then realize that they can opt out of only some uses. The main opt-out registries focus on research. Opting out of *all* research, while remaining in the archives for other purposes, is not necessarily a meaningful choice (Holm and Madsen 2009). Patients might wish to support academic research into cancer, but not commercial research into psychiatric diseases. Or they might wish to support research, but not administrative control regimes aimed at monitoring their physicians. If the point is to let patients influence how their data are used, much more fine-grained and dynamic options are needed (Holm and Ploug 2017; Kaye, Whitley, Lund et al. 2015). The most common experience when interviewing patients, however, is that they want to focus on their own treatment, not on administering data reuse. Options aimed at data control are likely to serve only the most resourceful citizens. Responsibilization of the individual nevertheless remains the standard response in data politics.

Informed consent in general does more to protect the institutions and companies thriving on data sharing than the individuals providing their consent (Hoeyer and Hogle 2014; Hoeyer 2005; Hoeyer and Tutton 2005; see also Rothman 1991). This point remains relevant for the ethics of data-intensive medicine as well. With the open data movement and the FAIR principles, the use of informed consent as a means of protection becomes even more ineffective. FAIR means that research participants first provide informed consent to specified research projects, and then when the project ends, the data are to be made available to other researchers with other research questions in anonymized form. A pharmaceutical company or a competing academic

research group might use data from an academic study for purposes that run directly against the ones listed on the original consent form. In such cases, FAIR is not *fair*. Danish policymakers claim that anonymization constitutes a technical fix to the problem with informed consent, but to reuse data generated for a different purpose where there was an explicit consent is not respectful. It is not recognizing people as contributors to research.

Furthermore, if enough data are available, nobody is anonymous. Moreover, people have interests other than controlling their own data. Predictive data tools target people regardless of whether they were part of the group providing consent in the first place (Taylor, Floridi, and van der Sloot 2017; Taylor 2017). Many research projects facilitate data predictions that can target individuals based on particular traits, such as their weight, blood pressure, sexuality, ethnicity, income, or place of residence (Holmberg, Bischof, and Bauer 2013; Amelang and Bauer 2019). In some cases, such tools can deprive groups of people access to benefits, treatments, or insurance. Data tools that are not designed well may even hit the wrong target (Altman 2019; Lipworth, Mason, Kerridge, and Ioannidis 2017). When data profiles are traded in automated systems, individuals can have their identities mixed up with strangers without knowing, and with no opportunity to object (Pasquale 2015). In some cases, it might not be privacy breaches, but invalid conclusions based on the wrong data, which constitute the primary risk to patients.

There is no safe way to administer your data in data-intensive health-care, not even for the data-literate individual. Absence of data about a person is also a data profile, as Lone discovered when she had her driver's license cancelled because she tried to "protect" herself by not sharing her data (see chapter 2). I once called a data broker to find out why I received a certain invitation via surface mail, only to learn that they were selling my profile as a person who is "*not* on Facebook, Twitter, or LinkedIn." It may all sound relatively innocent, but in automated systems of law enforcement, a data absence can also translate into the profile of "likely to be criminal" or a "terrorist," and in credit scoring and in the insurance industry, data absences can be very expensive (Sætnan 2018; O'Neil 2016). How should informed consent ever protect people against these harms?

When data operate as cogs in multiple machines, including machines aimed at monitoring and controlling people, the very ambition with data reuse can be to overrule individual choice, and then informed consent is little more than a shimmer of false control, generating massive amounts

of data work. I described in chapter 4 the impossibility of reading terms of agreement before consenting, and how it left me with no real choices. Instead, click-to-consent involves an intolerable responsabilization of citizens. When insisting on consent, the healthcare system has come to mirror the absurdity of the wider space of the Internet, where agreeing to cookies is a precondition for access to platforms with a voracious appetite for people's data (Fourcade and Kluttz 2020). There is a dire need for tools other than data literacy and individual "choice" if governments wish to protect—and respect—citizens in data-intensive societies.

The ethics of data-intensive healthcare, therefore, is in need of an alternative to the trope of individual responsibility. I stated in chapter 6 that I believe that research must be honest about the values shaping its findings. My own research—and my quest for a *response-able* healthcare system—is informed by ideas about justice (Reardon 2017), solidarity (Prainsack and Buyx 2017), and recognition (Taylor 1994). These are values that focus on ensuring equal opportunity, conserving common goods, and showing respect for individual differences. The point of combining these ideas is to acknowledge that people have individual stakes in data sourcing, but not to hold them individually responsible for living in systems that they cannot control. I believe that policymakers who wish to preserve legitimacy could benefit from focusing on the values of justice, solidarity, and recognition. It could inspire them to build more socially robust systems. Data *can* serve solidarity, justice, and recognition. Data *can* be considered what Widdows and Cordell (2011) call a "community good," increasing in value (and value dimensions) through aggregation. It takes concerted effort, however, as well as a willingness to monitor and explore the unintended consequences of data integration.

To ensure continued legitimacy, I believe that there is a need to begin thinking in much more radical ways about potential solutions. Such solutions should preserve aggregated data as a common good, ensure fairness, and make people with diverse values feel recognized. I present a list with a few suggestions in table 7.3. They are intended as prompts or, you might say, as provocations. I do not present them as a new coherent governance model because no government would adopt such a model anyway. I outline them only as ideas so they may circulate and perhaps translate in locally meaningful ways. I do not wish to replace local innovation with standard proposals. The point with this list is merely to suggest that guided by justice, solidarity,

Table 7.3

A nonexhaustive list of alternative ethics framings building on solidarity, justice, and recognition

Prioritize clinical uses of data over reuse of data for secondary purposes and make sure that reuse of data does not endanger patient interests. Make priorities between different types of reuse. Even legitimate interests in detecting various forms of fraud might backfire if people lose faith in the healthcare system and the doctors and nurses treating them.

Give access to health data for research purposes only on condition of a proven ability to understand the data. If researchers do not understand data well, they produce useless (or even potentially harmful) results. Make sure to fund documentation of metadata where needed.

Invest in user interfaces ensuring that patients are granted proper options of choice, and build those options on careful research into the hopes and concerns of the affected people rather than the hunches and gut feelings of civil servants and IT developers. People should feel recognized and respected when seeking to influence their own data representations, and the available options must be as easy to use as the interfaces through which data are sourced in the first place.

Retain options for the use of population data for research purposes aimed at promoting the common good on the condition that the research can be carried out in ways that ensure the anonymity of each individual.

Ban data profile markets with very few, well-regulated, and transparent exemptions.⁴ In what sense can selling people's data profiles ever be seen as representing a common good? Selling data profiles has undermined a number of other common goods, such as independent media, trust in healthcare providers, and collective sharing of risk in the insurance industry.

When making data investments, consider what economists call "externalities" and make carefully balanced investments with an eye to the need for repairs and renewal of equipment. Do data technologies carry the risk of technology lock-in and monopolies? Do they depend on technologies that carry high environmental risk? How much energy will data storage consume, and what is the climate impact? Can they be used for surveillance? Do the technologies emerge through exploitive global relations?

and recognition, new regulatory solutions may transpire—solutions that acknowledge the need to protect individuals, prioritize among data reuses, help build more robust data analyses, make citizens feel respected and accommodated, and harness the benefits of data while acknowledging the costs.

With these alternative framings of ethical issues, I suggest focusing on making data reuses *fair* so that data provided in good faith are not later used against individuals, and already disadvantaged groups do not face greater risk than others. I suggest administering data resources with care as collective goods to be consumed in *solidarity*. And I suggest working to

ensure that people feel *recognized* and their expectations of confidentiality are respected. The list of suggestions in table 7.3 might look far from feasible in the current political atmosphere, but I maintain that they are more realistic than the imaginary “total disruption through datafication,” which is featured in many policy papers, strategy papers, and consultancy reports.

THE POLITICS OF INTENSIFIED DATA SOURCING IN HEALTHCARE AND BEYOND

The data-political dynamics that I have identified in this book relate to a particular sector and build on work in a particular context of highly integrated data infrastructures. Still, I believe that some of these dynamics have a broader relevance for datafication in other contexts and other social arenas in Denmark and beyond (Amoore & Piotukh, 2015; Madsen, Flyverbom, Hilbert, & Ruppert 2016; Petersen, 2019). Data promises sweep across not only health, but also *education* (Kwet 2019; Hartong and Förschler 2019; Fernandez and Lutz 2019; Gorur 2011), *social work* (Høybye-Mortensen 2015; Lyneborg 2019; Parton 2008), *media* and *entertainment* (Fuchs 2016; van Dijck 2013), *law enforcement* and *defense* (Adelman 2017; Möllers 2021; Slayton 2021; Shklovski, Troshynski, and Dourish 2015; Haggerty and Ericson 2000; Grünenberg 2020; van Eijk 2021), *migration* and *biometric border control* (Grünenberg 2020; Trauttmansdorff and Felt 2021; Grünenberg, Møhl, Fog Olwig, and Simonsen 2020), *credit* and *finance markets* (Pasquale 2015; O’Neil 2016; Riles 2013; Mackenzie 2021), and *city planning* and *traffic control* (Halpern 2014; Poirier 2021). Data intensification characterizes both public and private sectors. Still, even a country as data-intensive as Denmark is not data-driven. Rather, it is a data-pursuing society. The governance of human lives should not be data-driven—it should *use* data. With care. It involves learning to look *at* data and what they do, not just to *use* data as tools of observation. I am confident that this is relevant not only in Denmark, and not only in healthcare.

Data promises gain political strength partly due to a strong tradition for searching for technological solutions to societal challenges. Technological solutions are supposed to be simple fixes. STS scholar Andrew Barry (2001) notes: “We live in a technological society . . . to the extent that specific technologies dominate our sense of the kinds of problems that government and politics must address, and the solutions that we must adopt” (2). It

is better to look for *socially* robust solutions than for technological fixes. To investigate social dynamics carefully implies also listening to dissenting voices. In the messianic space of semireligious dataism, people who divert from the standards designed by a tiny minority of tech experts are treated as renegades. Societies that wish to embrace new technological opportunities must be able to build more accommodating solutions; otherwise, they risk stimulating dichotomous spaces of truth-telling where opposing parties are unable to agree on anything. The major threats to data intensification might be the pompous and self-contained data gospel, more so than technological failure; and claims of neutrality in data forecasts, more so than acknowledgment of doubts and values.

Most people expect technologies to fail occasionally, and they know that experts have opinions. To have faith in technology, citizens must trust the good intentions of the companies and governments. When politicians and industry representatives abuse data to legitimize decisions that serve their self-interest, when complaints from citizens and clinicians are ignored or sidestepped as coming from dimwitted laggards, when quick and dirty analyses proliferate, and when policymakers ignore local knowledge because it does not feature in their data set, then everything that citizens and patients stand to gain from data intensity is at risk. When instead policymakers, administrators, and clinicians ask the right questions, when they care for those who are in need, when they face mistakes with openness and courage, then data can come to serve the interests of future patients, in all their diversity. With “Data Wisdom,” I contend, it is possible to build healthcare systems that meet this challenge.

This is a section of [doi:10.7551/mitpress/14926.001.0001](https://doi.org/10.7551/mitpress/14926.001.0001)

Data Paradoxes

The Politics of Intensified Data Sourcing in Contemporary Healthcare

By: Klaus Hoeyer

Citation:

Data Paradoxes: The Politics of Intensified Data Sourcing in Contemporary Healthcare

By: Klaus Hoeyer

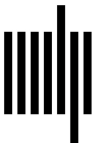
DOI: [10.7551/mitpress/14926.001.0001](https://doi.org/10.7551/mitpress/14926.001.0001)

ISBN (electronic): 9780262374156

Publisher: The MIT Press

Published: 2023

The open access edition of this book was made possible by generous funding and support from MIT Press Direct to Open



The MIT Press

© 2023 Massachusetts Institute of Technology

This work is subject to a Creative Commons CC-BY-NC-ND license.
Subject to such license, all rights are reserved.



The MIT Press would like to thank the anonymous peer reviewers who provided comments on drafts of this book. The generous work of academic experts is essential for establishing the authority and quality of our publications. We acknowledge with gratitude the contributions of these otherwise uncredited readers.

This book was set in Stone Serif and Stone Sans by Westchester Publishing Services.

Library of Congress Cataloging-in-Publication Data

Names: Hoeyer, Klaus, author.

Title: Data paradoxes : the politics of intensified data sourcing in contemporary healthcare / Klaus Hoeyer.

Description: Cambridge, Massachusetts : The MIT Press, [2023] |

Series: Infrastructures series | Includes bibliographical references and index.

Identifiers: LCCN 2022019995 (print) | LCCN 2022019996 (ebook) |

ISBN 9780262545419 (paperback) | ISBN 9780262374163 (epub) |

ISBN 9780262374156 (pdf)

Subjects: LCSH: Medical informatics—Denmark—Case studies. | Medicine—Denmark—Data processing—Case studies. | Medical policy—Denmark—Case studies.

Classification: LCC R858.A3 H64 2023 (print) | LCC R858.A3 (ebook) |
DDC 610.28509489—dc23/eng/20220830

LC record available at <https://lcn.loc.gov/2022019995>

LC ebook record available at <https://lcn.loc.gov/2022019996>