Pedersen, Asbjørn Malte; Bossen, Claus (2025): Making healthcare data-driven: Ordering, experimenting with, and discovering data. Infrahealth 2025 - Proceedings of the 10th International Conference on Infrastructures in Healthcare 2025. DOI: 10.48340/ihc2025_p010

Making healthcare data-driven: Ordering, experimenting with, and discovering data

Asbjørn Malte Pedersen & Claus Bossen
Department of Information Studies, Aarhus University
ampedersen@cc.au.dk; clausbossen@cc.au.dk

Abstract. Amid growing ambitions to make healthcare data-driven, the practical work and challenges involved in such transitions remain underexplored. Drawing on four years of ethnographic research in a public Danish healthcare Business Intelligence Unit (BIU), this paper examines the everyday data practices involved in making the healthcare organization data-driven through a case of reorganizing human resource data and developing reporting tools for a workplace well-being initiative. We analyze three interrelated processes - ordering, experimenting, and discovering - that characterize the BIU's efforts to render data actionable. Rather than depicting data-drivenness as a linear or purely rational process, we show how it involves iterative reconfigurations of infrastructure, reverse-engineering opaque vendor logic, and creatively excavating new data traces. These findings highlight the experimental and situated nature of becoming data-driven and offer a practice-based perspective on 'becoming data-driven' in healthcare organizations.

Introduction

Over the past decade, the notion of data-driven healthcare has gained significant international traction, spurred by the ongoing digitization of healthcare. Becoming data-driven is generally understood as a strategy for healthcare institutions to harness the power of data to improve decision-making, enhance patient outcomes, optimize workflows, and advance research (Grossglauser &

Saner, 2014; Madsen, 2014; Ruckenstein & Schüll, 2017). While the ambitions of making healthcare data-driven thrive in strategies and research (Hoeyer, 2023; Mayer-Schönberger & Cukier, 2013), it is less clear what this means in practice. The somewhat diffuse notion of 'data-driven' can broadly be defined as the "property of being propelled, guided, or controlled by data" (Fischer et al., 2023, p. 4), a concept originally applied to specific functions like marketing but today, through digitization, applied to whole organizations (Fischer et al., 2023). Denmark is widely recognized as one of the most digitally advanced countries, with a highly digitalized public sector, robust IT infrastructure, and digital health services (European Commission, 2022; OECD, 2023; WHO, 2024). Strategically, data plays a central role in healthcare, supported by extensive national health registers that cover the entire population (Hoeyer, 2023; Sundhedsdatastyrelsen, 2024). Primary and secondary use of data is seen as two sides of the same coin, and data is, for example, by the Danish Health Data Authority (Sundhedsdatastyrelsen, 2024) positioned as fundamental to addressing healthcare challenges and advancing treatment, analytics, and research. The above strategies often see 'becoming data-driven' as rational and linear practices (Kornberger et al., 2025), but there is limited research on how this unfolds in practice.

Taking this as our starting point, we highlight the non-linear and concrete practices of 'becoming data-driven'. This study is based on ethnographic fieldwork conducted in a public healthcare Business Intelligence unit (BIU) in one of Denmark's five healthcare regions. The BIU extracts, repurposes, and delivers data to five hospital units within the region. In this paper, we specifically focus on the work involved in reorganizing human resource (HR) data in a data warehouse and producing reporting tools for a project called 'The Attractive Workplace'. We identify three central characteristics of the work involved in making the healthcare organization data-driven: the processes of ordering, experimentation, and discovery.

Background

Despite the hype, research into data-driven organizations is fragmented, and the concept itself, as mentioned above, is diffuse: "Defining "data-driven" resembles the task of catching a jellyfish with a knitting needle in a moving boat" (Kornberger et al., 2025, p. 187). In their review of the field, Fisher et al. (2023) cite Martin & Powell (1992) for the role of data in organizations: "[Data is] the raw material of organizational life; it consists of disconnected numbers, words, symbols, and syllables relating to the events and processes of the business" (Martin & Powell, 1992 in Fischer et al., 2023, p. 3). In the review, Fisher et al. (2023) identify both a great variety of understandings of what data-driven means as well as of the intrinsic relations between data and organizations. Research into the use of data to support management and drive organizational change goes back at least to the 1960s, with research into computerized decision support systems. A field, which from the 2010s evolved into two partly overlapping strands: On the one hand, knowledge management and change management research, and on the other, business analytics research (Berndtsson et al., 2020). Another strand of research into the use of data was conducted under the umbrella of performance management, directed at managing organizations through the monitoring of key performance indicators (Moynihan, 2009; Pollitt, 2018; Smith, 1995). Today, these fields are accompanied by research into Big Data and artificial intelligence (Kitchin, 2014). At present, there are different general descriptions of what 'data-driven' means: The American Hospital Association (2020) points towards people, processes, and technologies, whereas Fischer et al. (2023), mentioned above, identify five core dimensions in data-driven organizations which managers must attend to: data sourcing and sensemaking, data capabilities, data-driven culture, data-driven decision-making, and data-driven value creation. As Kornberger et al. (2025) state, data-drivenness has an aura of rationality and factuality, which, however, they question: The assumptions that data will inductively speak for itself and decisions will be based on evidence run into the limits of rationality, they argue.

In this paper, we partly see data-drivenness as a pursuit to base decisions and management practices on evidence and rationality, but more importantly, we also suggest understanding it as a process of experimentation and exploration (Bonde et al., 2018; Danholt et al., 2019; Seidelin et al., 2020; Wallenburg et al., 2018). One insight that has come out of performance management research is that identifying the key performance indicators through which an organization's performance should be monitored and managed is a critical step. Within healthcare, performance management is linked to, for example, value-based healthcare initiatives, which a literature review concludes are often small initiatives of an experimental nature (Van Elten et al., 2023). Hoeyer (2023) regards Denmark's present focus on making healthcare data-driven – which he calls 'intensive data sourcing' - as a large-scale societal experiment. Hence, these scholars point to the critical and often experimental aspects of making data central in organizational decision-making and development.

We approach the notion of 'becoming data-driven' as practices of experimenting and exploring with an interest in what kind of work this involves. Our basic starting point is that data is not "out there to be gathered" but rather has to be created and constructed (Kitchin, 2014, p. 2). In this vein, we have an interest in the mundane practices and processes of creating data, including generating, filtering, disseminating, visualizing, and constructing data sets. Within healthcare, data work by physicians, nurses, patients, and data analysts is a crucial element in efforts to repurpose clinical and administrative data to improve healthcare efficiency and quality (e.g., Bertelsen et al., 2024; Fiske et al., 2019; Knudsen & Bertelsen, 2022; McVey et al., 2021; Pedersen & Bossen, 2024a;

Torenholt et al., 2020). From this research and similar research on data science workers, it is clear that data work is collaborative (Zhang et al., 2020), involves intuition, craft, and creation of data (Muller et al., 2019), as well as emotions (Choroszewicz, 2022). Thus, making healthcare data-driven involves humans and organizational processes in manifold ways.

Methods

This paper is based on a four-year ethnographic study of a healthcare BIU (2021-2024), which follows the call to make visible the efforts, tasks, and knowledge required of working with data (Bossen et al., 2019; Fiske et al., 2019; Møller et al., 2020). Here, we specifically focus on the practices of BI developers (BID - occupational title for specific BI employees. See Pedersen & Bossen, 2024b) who collaboratively maintain a regional data warehouse, develop reporting and visualization tools, and work on data models. Following an ethnographic approach (Hammersley & Atkinson, 2007), the first author conducted fieldwork in the BIU and related hospital wards (approx. 92.5 hr.) and 20 semi-structured interviews with BI staff and management (approx. 16 hr.). Lastly, extensive research of documents and artefacts was conducted to explore the policies around the BIU in greater depth. All field notes were written into full accounts, and interviews were transcribed verbatim for analysis.

For this paper, we conducted a thematic analysis according to Tracy's (2024) 'phronetic iterative' approach. This approach emphasizes a dynamic, back-and-forth movement between data and theory to generate pragmatic, context-sensitive knowledge that is both theoretically informed and practically relevant. We first produced primary codes from the interviews and observations, which focused on central data work practices and challenges in making healthcare data-driven. These codes were then critically examined in a secondary cycle of axial coding to synthesize the findings. We identified three central themes (reflected in the subtitles of the 'Findings' section), which we suggest understanding as processes of ordering, experimenting, and discovering. Both authors discussed the codes and findings to refine the analysis and achieve intercoder reliability. In the following sections, we first present the case and then the central findings from our analysis.

Findings: 'The Attractive Workplace'

In 2022, the BIU's management board approved a new project called 'The Attractive Workplace' with a trial period of 1 year. The project commenced due to an increased focus on workplace well-being and staff retention within the regional healthcare system. A management group identified seven themes related to the subject: overview of staff, sick leave overview for the management, shifts, recruitment and staff retention, well-being, education, as well as labor costs and use of substitutes. The BIU's role was to facilitate data support, update the HR data model, and develop reporting tools that could be used in the work on 'The Attractive Workplace'. However, at the start of the project, challenges occurred due to scattered data and private data providers who obscured and delayed data processing and delivery.

In the following, we present three instances that highlight how the BIU overcomes the challenges of making the healthcare organization data-driven. We specifically focus on the rebuilding of an HR data model and the development of two reports focused on 'short- and long-term sick leave' and monitoring of student nurses' work.

Ordering: Reconfiguring eroding models

Developing new reporting tools was not simply a matter of curating and visualizing already available data but also of ensuring that the data model was in place and operating reliably. However, data models can erode over time due to ad-hoc repair and lack of documentation, a process that had come to a point where the BIU had to reconfigure its HR data model.

The HR data mainly consisted of different data points about employees, such as occupation, employee status, workplace, shifts, payment, etc. According to a BID, this data had not particularly aroused the interest of the healthcare organization before 'The Attractive Workplace' project. This prompted a renewed focus from the organizational management and other staff members who asked for more HR data. However, the HR data model - which defines what data exists, how it is organized, and how different data is connected - was at this point seven years old. It had been built at the beginning of the BIU's activities, at a time when they did not have the same standardized development guidelines as today, such as instructions, tests, and mandatory documentation. So, even though the BIU had maintained and repaired the data model throughout the years, this became increasingly challenging to do, as a young BID explained during an observation:

> "Errors occurred in the old system, which were challenging for us to correct", she said. "In the system? Or how the tables were connected or…?", I asked to understand. "Yes. It was so opaque. That is, we could just barely fix it, and it was challenging to figure out why errors occurred. And one thing is that I could not make sense of it, but that was also the case for those who had been working on it previously. One of them just had his 10th anniversary with data work in the region. So, it was not just me who thought it was challenging", she explained. (BID, field notes)

While the data model had worked properly at one point, the lack of documentation and maintenance, combined with patch fixes and ad-hoc repairs over time, had made the model more complex and opaque to the BIDs. As the demand for HR data grew and the model had become too unstable, the BIU gave the HR data model an overhaul: “So, we had to reorganize it, because it has been changed so many times that we were kind of forced to start over”, a BID explained during observations. This work involved constructing a new data model according to their current standards of modelling: Loading relevant data sources into the data warehouse, reorganizing the data into tables, and mapping the data points and their relationships, as well as how data was used. Yet, the reorganization was more time-consuming than anticipated, as they had to rework the model and reorganize the data from scratch. At the time of observations, it had taken 1.5 years and was, at that point, almost done. According to the BIDs, all this work on a new data model was beneficial, as it would provide the end-users with “better” and “more correct data”, because errors would not occur as frequently as before. Moreover, the structure of the data model and the data relationships would be more transparent to themselves and other users in the future, as a lot of work had been put into making their choices and the data relations visible through documentation and mapping.

However, while reconfiguring the HR data model would fix errors and make it easier to maintain in the future, it also introduced other potential errors. As older reports used for monitoring and decision-making were linked to the existing HR data model, they queried and visualized data based on the logic of organization of tables, fields, and constraints defined by this – now to be replaced - model in the data warehouse. In other words, the reports were dependent on the model to tell them what data existed, how it was organized, and how different pieces of data connected. These links – and hence, reports - would break down when the new data model was deployed and taken into use. To avoid a breakdown in organizational workflows and procedures supported by the ‘old’ reports, the BIDs initiated a process where they maintained both the old and new data models. They then, one by one, rebuilt and linked the reports to the new data model. Some of these reports were easier to fix than others, as the data organization and tables did not look too different from the old data model. However, others required more work by the BIDs to make them function as before, as some reports were created early in the BIU’s formation, before a standardized development process was in place; since then, BIDs are required to follow set guidelines for development, user input, interface, and documentation. These guidelines were put in place to ensure transparency and make it easier for other BIDs to fix errors, even if they have not been part of the production of it.

The reconfiguration of the HR data model highlights the dynamics of how growing organizational demands for data can expose the hidden erosion of infrastructures, where years of undocumented models, repairs, and ad-hoc fixes accumulate into a technical mess. Although the reconfiguration aimed to create a more transparent, maintainable, and reliable model, it also introduced the risk of cascading errors across the BI infrastructure, as older reporting tools were tightly linked to the original model's structure. To prevent breakdowns in organizational workflows, the BIU maintained both old and new models in parallel while also rebuilding and reconnecting reports, illustrating how reconfiguring and repairing are both technical and organizational challenges.

Experimenting: Reverse engineering unknown data calculations

Part of the reorganization of the HR data also meant that data could be updated weekly or even daily instead of monthly as before. This was, for example, the case with data on 'sick leave'. While this data is produced onsite at the hospitals, its journey from production site to the data warehouse was more intricate than other data sources. Department managers, be it head physicians, head nurses, or others, would enter data on employees as well as their absence and shifts into a 'shift schedule' software program. This software was provided by a private software company (PSC) that collected the data. The data would then be transferred to another private data company (PDC) specializing in salary and staff solutions for the public sector. The PDC 'enriched' - a process of enhancing data's value, usability, or interpretability by adding context, structure, or related information (Muller et al., 2019) - the employee data before making it available to the BIU and other healthcare staff. Moreover, the PDC would perform calculations that, among others, determined if an employee's sick leave could be defined as short- or long-term leave. Such tasks were possible to conduct for the PDC because they only had to make monthly deliveries.

The BIU encountered two challenges in this regard: 1) Because of the intricate journey and the time it took to manage data for each private actor, the BIU would only receive these data monthly, and 2) throughout the journey, each private actor would or would not enrich or in other ways manipulate the data. However, these enrichments were opaque to the BIU with respect to whether they had been conducted or not. In other words, the BIU could not validate the data calculations, which meant they could not explain them to their users.

To shorten the period, the BIU took over the task of making the calculations and definitions themselves. They still received the data from the PDC, but the level of enrichment changed: "They still do a lot of stuff [to the data] and it helps a lot. […] But it is just nicer if we know exactly how it is done" (BID, field notes). Subsequently, the BIU did their own calculations and definitions, which ideally would reproduce the same results as the PDC to ensure accuracy as well as consistency, so that trends could be interpreted over time. However, the PDC's calculations were opaque, and the BIU did not have any proper guidelines to follow. As a BID explained:

> I wish there were more openness. Or that it was more transparent. Because when you try to talk to [the PDC], you do not talk to those who work on the data. Instead, you talk to a salesperson who does not necessarily know anything about it. And it is extremely difficult to get to talk to those who work on the data. They are probably not allowed to tell us what they do, because they earn money from it. (BID, Field notes)

Instead, the BIU had to figure out for themselves how to mimic the PDC's calculations to get similar results. To do this, they first collaborated with the HR department, which provided them with "business logic". Subsequently, they would perform random checks and compare their own calculations with the results from the PDC to see how well they matched. In most cases, they were able to reproduce the PDC calculations and results, which, additionally, would cause fewer errors, as the BIU now knew and could explain them. However, this was not the case with 'long- and short-term sick leave' data: "Before, it was just something like there is 'long-term sick leave' which is longer than 'short-term sick leave' without anyone being able to see or understand the calculations behind it" (BID, fieldnotes). While the BIU sought help on the matter, it turned out that even the HR department found the categories to be ambiguous: How many days could an employee be ill before it should count as long-term? How ill should the employee be? Which kind of diseases should count? And how to count half a day? To investigate the issue further, the BIDs had to make certain decisions completely transparent to their collaborators: They made drawings on a calendar, sketching out different scenarios, and sent them to an employee in the HR department, asking, "Do you consider this long-term non-attendance? Yes, or no?". This helped render their own decisions visible while also validating these in collaboration with HR. In the end, however, the BIDs could not get their calculations and results to match the calculations of the PDC:

> "And because they could not tell us how they did their calculations, then we just agreed that this is what we go with [...]". I asked her if that meant the tables and data would look different from before. "They could", she answered, […] "Many of them are pretty precise just with fewer errors. But this, long- and short-term, will be fundamentally different" (BID, fieldnotes)

The BIU in the end settled for a pragmatic closure instead of endlessly chasing an inaccessible standard. While this in some cases produced minor deviations that were seen as benign or even as an improvement, as the BID above indicated, it also caused a substantial shift in how the 'long- and short-term sick leave' metric was defined. What is now being measured is redefined altogether.

Thus, the effort of re-engineering unknown calculations involved not merely reproducing technical outputs but reconfiguring the very definitions and calculations of organizational metrics. The BIU's attempt to take over and replicate the opaque data processes previously handled by private vendors exposes a deep dependency on external actors not just for infrastructure, but for interpretive and operational knowledge. As the BIU confronts the opaque calculations and withheld business logics of the vendor, the BIU engages in collaborative and pragmatic work to re-engineer meaning and restore internal accountability. This shift illustrates how data calculations are not simply transferred but transformed when brought in-house.

Discovering: Excavating data, constructing indicators

It is often assumed that data is available, stored in repositories, and ready for repurposing. However, data extraction, formatting, and storage often require cumbersome and extensive work (Bonde et al., 2019) which sometimes involves excavating data and constructing indicators from unexpected data sources.

This was evident, for example, when the BIU initiated the development of a new HR report to support educational purposes in relation to student nurse interns. As a BID explained, the group of data workers thought staff data was available, but looking into the HR data, they there was no data available on student nurse interns as they were not directly hired by the regional healthcare system. Starting from a blank slate, they had to figure out where to find data traces of the nurse interns' work and what they could do with it. Consulting the advisory group for the report, they learned what type of tasks the nurse interns would conduct during their stays on different wards, and this informed their ongoing search for data. They began to excavate data from the Electronic Health Record (EHR) and found two traces: Dictation and healthcare content (HCC – SFI in Danish). HCC is produced to support and document clinical processes whenever a patient has been consulted, and most of the students would take dictations and produce HCCs in the regional EHR during their internship. However, it was not the content of the dictations or HCC that was interesting to the BIDs. It was instead the mere activity of these tasks, how many times they had been conducted, when, where, and by whom. Linked with other data, these traces laid the foundation for two reports that could provide an overview of their workload. The purpose of the reports was to support managers responsible for the interns' educational elements, providing them with an overview of what kind of work the individual nursing intern had done: What types of HCCs had been produced, how many, and when? This could be used to compare the interns' activities for educational purposes to ensure that they had been exposed to different HCC-related tasks.

This example demonstrates how data might not be readily available but must be excavated and constructed from unexpected data sources in creative ways to become available for repurposing. Yet, this also emphasizes the challenges of developing representations of work. In this case, the incomplete data on the nursing interns only renders their data work activities visible. The student nurse interns' care work with patients would, for example, be rendered invisible. The BIDs reflected on this problem during a self-organized data conference in one of the regional hospitals while presenting these two reports. A person in the audience acknowledged the usefulness of the reports but wanted to know more about the BIDs' ethical considerations regarding data and the limits of the report representations. The BID who had presented the report answered that they of course had these discussions, but that the reports were only intended as "dialogical devices": The purpose was not to use the data to indicate if the nursing interns were doing enough, but rather to get an overview of some of the work they already had encountered. The BID emphasized that it was important that the manager worked holistically and considered other aspects of nursing work not represented by the report, using all their knowledge of the individual interns.

This underscores how health data is not passively available but actively made through creative and collaborative processes. Rather than drawing from pre-existing HR records, the BIU team had to excavate indirect digital traces of nursing interns' activities within clinical systems to construct indicators. The resulting reports, which had a limited view of the intern's work, were to serve as dialogical tools to support managerial reflection, highlighting both the potential and the constraints of data-driven representations in healthcare settings.

Concluding Discussion

In this paper, we have investigated the efforts of a healthcare BIU in making healthcare data-driven and provided three examples of how such efforts were not a linear and rational process toward the delivery of data as evidence. Instead, we see how data models erode over time and require repair or even, as in the first case, a total reconfiguration and subsequent anticipatory efforts to avoid new cascading errors. In the second case, the delivery of data more frequently entailed the BIU taking home part of data management, and in particular, reverse engineering and mimicking the calculations previously done by a private company. In the end, the result was a new baseline for 'sick leave'. Finally, in the third case, data had to be excavated from the large pool of EHR data to abstract indicators on intern nurses' training. Based on these findings, we suggest understanding 'making organizations data-driven' in these cases as processes of ordering, experimenting, and discovering. Such a perspective foregrounds the messiness and obscurities as well as the negotiations and pragmatic choices that are involved in working with data. This further emphasizes how data through experiments – and the involved practices and technologies – come to constitute what can be seen and known, which potentially can have organizational consequences.

Thus, our findings align with other research that points towards the aspects of discovery and experimentation when working with data in healthcare (Bonde et al., 2018; Danholt et al., 2019; Hoeyer, 2023; Wallenburg et al., 2018), industrial vocational training (Seidelin et al., 2020), and education (Ratner & Gad, 2019). We do not suggest that becoming data-driven is not a strive for evidence-based and rational decision-making, but we stress that a complementary aspect of such efforts is that of ordering, experimenting, and discovering. This has implications for how we understand what 'becoming data-driven' means and how it can be investigated, as well as for the practical implementation of data-driven healthcare:

Managers and politicians must set aside resources that allow for these necessary aspects and processes to incorporate it in planning.

Acknowledgments

We would like to extend our heartfelt gratitude to the staff and management at the healthcare BIU for their time, patience, and generosity. This research is supported by the Independent Research Fund Denmark, Grant 0132-00200B "Making data work visible".

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