# Co-designing Data Experiments

Domain Experts' Exploration and Experimentation with self-selected Data Sources

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Today, organizations have to deal with multiple heterogeneous data sources from different systems and platforms to maintain and develop their services. Therefore, there is a need for tools to support organizations to determine what data sources can advance and innovate their services. This paper reports on how we addressed this need by designing and implementing two design tools – the Data Sphere and the Data Experiment Template – to support domain experts' exploration with different data sources which they selected themselves. We find that (1) domain experts' exploration of data sources make the cross-organizational dependency of data and data work visible; (2) the value of co-design becomes evident to address this dependency; and by that, (3) the data became 'design things', that means data are object of design that at the same time create a space for members of the organization to together explore how to use data to innovate their services.

**CCS CONCEPTS** • Human computer interaction (HCI) • Collaborative interaction • Empirical studies in HCI

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## 1 INTRODUCTION

Several scholars have pointed out that we are living in an increasingly connected world as we continue to interact with digital technologies and data [26, 32, 39]. In this connected and data-dependent world, the vision for many organizations is to become more 'data-driven' to improve their own (data) work practices or support innovation of digital services [36]. Currently, such exploration and experimentation with data often requires highly specialized IT skills to make sense of what data sources are useful and how they might support the innovation of processes, products, and services [3, 4, 42]. This prevents non-ICT domain experts from engaging with data in innovative ways [5, 25]. To support that vision, there is a need for tools that can help domain experts, especially those who are not IT-professionals, to explore and experiment with data and data sources in their organizations.

In line with the tendency to consider data as increasingly important in society, at work, and everyday life, there is an emerging body of work that explores "data interactions" within the ICT design research community (including conferences like DIS, CHI and CSCW). Notable examples are Feinberg [15] who has proposed a design perspective on data as a lens that emphasizes e.g. data collection as a design activity, Kun et al. [27] who examines how designers incorporate data work in the design process, and Dove [11] who examines the use of domain data in the context of co-design workshops. HCI scholars have also begun to examine how data can be (re-)presented in ways that enable domain experts to better make sense of data [12, 52], how data influences participatory processes [7, 45], and to explore ways to enhance people's awareness about wirelessly transmitted data [19]. A commonality for these studies is that the data sources used to enhance data literacy, prompt data work in design activities, and improve data visualization are predefined by the designers. Little is known how to support domain experts' identification, exploration, and experimentation of (new) data sources. This paper addresses this research gap by exploring how to encourage domain experts to help themselves on the road to identify and work creatively with data sources that could be useful to their work and in their organizational context.

We report on a study which was part of a larger 3-year action research project [20, 21, 40, 48]. The action research project was situated at Industriens Uddannelser (English: The Education Secretariat for Industry, henceforth: IU), which is an organization, based in Copenhagen, that works to maintain and develop vocational education and continuing education in the Danish Industrial sector. In the project we worked mainly with different domain experts at IU and their collaborative partners that in their day-to-day work at IU use and interact with data without being trained IT professionals (using databases, registers and collecting and sharing datasets within and outside of the organization). From here on in the paper, we will use the term 'domain expert' for such non-IT professionals that work with data. The herein reported on study had two overall objectives: (1) To develop a design process that could enable domain experts in the organization to identify, explore, and experiment with self-selected data sources, as a way (2) to advance innovation of data-based services in the organization. The study was designed as a process which included six workshops and three 'design inquiries' (see figure 1). The project was executed and evaluated in close collaboration with a project group that constituted five education consultants from IU. Education consultants comprise more than half of the workforce at IU. An education consultant is a domain expert within certain areas of vocational education and continuing education in the industrial sector in Denmark.

Specifically, this paper focuses on two of the workshops and two of the 'design inquiries' that brings attention to our proposed design tools. The first tool – The Data Sphere – aims to involve members of an organization to collectively design and generate 'data source ideas' for further exploration. The second tool – The Data Experiment Template – aims to support domain experts' ability to design and implement minor experiments with data sources in order to identify and evaluate the potential benefits and challenges of a given data source. On this basis, the paper's two principal contributions are a description of the two tools and how they were developed and how they can be used.

In this paper, we consider data as ‘design things’ [14] to acknowledge that data have ‘agency’ which to different extents modify the design process, its outcome(s), and its subsequent uses. We take inspiration from works that discuss data as a ‘design material’ to inform the design of our design tools, concepts and activities [13, 15, 23]. In the remainder of the paper, we detail our research activities and present our findings from the field. This paper contributes to the growing body of HCI research that considers data from a design perspective, by discussing three key insights from our exploratory design process: (1) the domain experts’ exploration of data sources made the cross-organizational dependency of data and data work visible; (2) the value of co-design to address these dependencies became evident; and by that, (3) the data became ‘design things’, that means data are object of design that at the same time create a space for the members of the organization to together explore how to use data to innovate their services. We also suggest directions for future work.

## 2 RELATED WORK

To consider data from a design perspective is still a nascent research area in HCI with a rather small catalogue of examples (including [11, 15, 28]). Most HCI research focuses on the design of (digital) interfaces and artefacts that can represent data and make it manipulable for domain experts and end-users [53]. However, common data visualization and data exploration design exercises do not (yet) encounter tools that support domain experts’ exploration and experimentation with different data sources, which they selected themselves. We address this gap by proposing two design tools for this purpose. To situate this work, we provide an overview of research that (1) touches upon challenges for work practices in cross-organizational and data interdependent settings, (2) consider data as ‘design material’, and (3) discuss design activities for data exploration.

### 2.1 Data Work and Co-design

We make use of the concept Data Work [2, 16, 17, 34] as a lens to help us think about the complexity that is included when considering identification and experimentation of data sources in an organizational context. The concept of data work has been coined to address the significant increase in the amount of work that is related to data in some sense, in recent years [2]. Data work has been defined as ‘any human activity related to creating, collecting, managing, curating, analyzing, interpreting, and communicating data’ [2:466]. By emphasizing these aspects of data-related work it becomes clear that it requires various encounters between people, technologies, and data, to make data 'work' (e.g. to enable data collection or application of useful data). As Bossen et al. [2] emphasize, these encounters are situated in particular places at a given time. When organizations wish to be able to work innovatively with data, it implies that the organization is aware of the many encounters and processes that go into its current data practices. Furthermore, it is important to recognize that the growing amount of data production, collection and usage have generated an increasing level of ‘data interdependence’ between organizations [45].Thus, the notion of data work is relevant as local knowledge about current data practices is needed in order to develop tools that can support an organization’s (and the people within it) exploration and experimentation with data.

Research has emphasized that the increased level of connectivity is challenging to comprehend and challenges how to co-design for such complex settings [8, 32]. For example, Degnegaard [8] argues that a single individual or organizational entity can no longer be pinpointed as the center of concern. Rather, he argues, it is necessary to include and account for multiple stakeholders because relations and interactions between stakeholders are dynamic and ever-changing [8]. To account for this high level of connectivity, in particular related to data work in a cross-organizational context, we have applied a co-design approach in our design work and approach for the domain experts when using the tools for experimentation with self-selected data sources. We refer to co-design in a broad sense, when ‘people come together to conceptually develop and create things/Things that respond to certain matters of concern and create a (better) future reality.’ [54:12].

### 2.2 Data as ‘design material’

The prevalence of data as a mine of information has led to enormous growth in collecting data that is used to influence decisions in various aspects of society and social life [18]. As one response to this tendency, the field of ‘Human-Data Interaction’ has emerged to emphasize research that examines how people interact with data [22]. The emerging body of work seems to assume that in order to get insights from data, people need to interact with data rather than passively consuming them [6, 33, 49]. This suggests that this form of interaction goes beyond data analysis and includes exploration of data [22].

HCI researchers have also begun to address the growing necessity to consider data as a fundamental component that shape how people (can) interact with technologies. For instance, Feinberg [15] propose a design perspective on data and show how data collection can be considered a design activity. Muller et al. [35] propose to develop a human-centred study for data science practices. Others have explored the role open data play for local policymaking processes [7, 24]. Together, these perspectives open up for a discussion how data can be considered a ‘design material’ in design and co-design, like other physical or functional dimensions in a design process.

Ehn [14] questions what it means to consider objects and things in design. Drawing on work by Latour [29], he emphasizes that ‘design things’ are essential when we deal with 'agency' of both human and non-human actants. To build on the perspective of data as design material, we consider data as 'design things' in this paper. We do so to acknowledge that data influence the design process itself, the design outcome of the design process, and its subsequent use. In the next section, we take a closer look at work that have attempted to understand the role of data and their representations in the design process.

### 2.3 Design activities for data exploration

Previous HCI research show examples of proposed different design concepts that aim to support people in making sense of data to enable them to work exploratively with data. ‘Data literacy’ is a concept, which describes the competencies around the use of data in order to reason, e.g. for problem-solving. As such, data literacy is increasingly considered to be a vital skill to gain and maintain in order to be able to make sense of data, data analysis, and data representations [9, 53]. The focus on data literacy has generated an interest in how people interpret and evaluate the effectiveness of digital data [10, 31, 38]. However, some Data Literacy studies have also examined ways to prompt more explorative aspects of making sense of data [51]. For example, Wolff et al. [51] designed a board game to support people’s understanding of ‘the relationship between data, the environment from which it derives, and the questions it can be used to answer’.

Another branch of research that attempts to foreground that data has agency and thus influence the design of digital interactions is Information Visualization. HCI researchers have examined how Information Visualizations can be applied in design projects as tools that can increase accessibility, and thus support people's engagement with and their understanding of data [11, 12, 50]. Others have attempted to prompt data exploration by appropriating a data science workflow to the early stages of the design process [27, 28].

The abovementioned research gives preference to visual materialization of data. However, Lupton [31] emphasizes a countertrend in HCI which explores how other senses can contribute to making sense of data. One example is FeltRadio, a system that intercepts WiFi and other 2.4GHz radio signals and translates these wireless bits to Electrical Muscle Stimulation (EMS) that a person can feel on their own body. Moving around, a person will perceive the amount of radio traffic and the corresponding signal strength on his or her body (through EMS). By rendering data perceivable to the human senses, FeltRadio becomes a tool to explore and reflect on data and (wireless) data sources [19]. More broadly, the attention to rendering data as 3D artefacts is known as Data Physicalization [23, 55]. The underlying assumption of this work is that multisensory experiences are better understood than those where only the visual dimension is used.

As an addition to this prior work, our proposed design tools expand the space for design activities for data exploration by supporting domain experts' exploration and experimentation with self-selected data sources.

## 3 RESEARH PROJECT AND METHODOLODY

The main objective of this study was to design a process that would enable domain experts at IU to identify, explore, and experiment with self-selected data sources. The research underpinning this article constituted the third and final intervention of a larger 3-year action research study at IU [20, 21, 40, 48].

Figure 1 below illustrates the process and the primary research activities consisting of six workshops (green) and three complementary 'design inquiries'(grey). The process was designed and implemented by the first author at IU. The initial part of the process focused on establishing an understanding of what constitutes data and data work for education consultants at IU. During this initial phase of the process, the project group interviewed their colleagues (design inquiry activity 1, figure 1), developed a mapping (workshop 2), and examined their own data practices in more detail (workshop 3). These initial stages helped to create a mutual understanding of what is considered 'a data source' and 'data work' in this context. However, in this paper, we focus on the later stage of the process because it focused on the generation of ideas for data sources that could be further explored, the evaluation and selection of these ideas, and the design of 'Data Experiments' which would support the domain experts' experimentation with their selected data sources. Specifically, we include data from the implementation of the Data Sphere (design inquiry 2), workshop 4, the execution of the Data Experiments (design inquiry 3), and workshop 5 (see highlighted boxes, figure 1).

The six workshops involved a project group, which comprised of five domain experts, who all worked as education consultants at IU (Employee 1-5). The five members of the project group had been appointed by their respective managers because they had shown particular interest in improving data work or new data-intensive technologies. Data and data analysis were central to the consultants' many everyday work practices. Prior to this study, IU had not explored new data sources and how these might benefit the organization in a structured manner. This was due to limited time and design capabilities, meaning that the organization and its members were not familiar with relevant design tools, how to prototype, or how to test different scenarios and possibilities. As a way to create organizational learning about beyond the project group, the process also included three additional 'design inquiries', which aimed at involving all organizational members in the understanding of what constitutes data in this organizational context (design inquiry 1), the generation of potential ideas for data sources (design inquiry 2), and the implementation of Data Experiments (design inquiry 3).

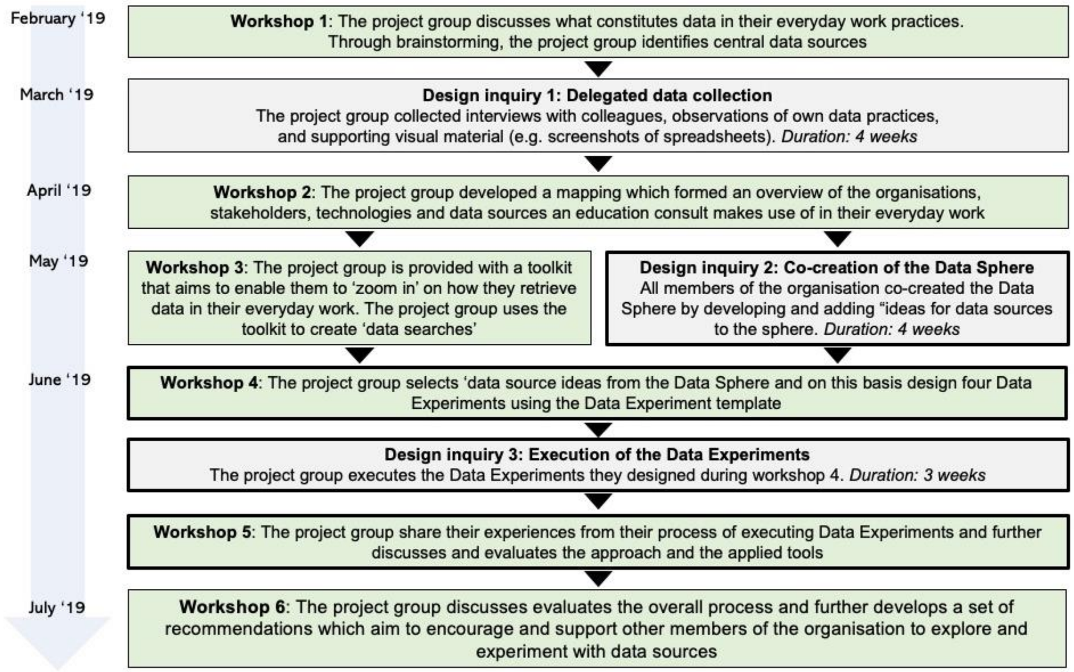


Figure 1: Overview of the design process and activities.

We adopted a research-through-design (RtD) approach as our process of inquiry in order to generate knowledge through our design activities [1, 56]. All workshops were video and audio recorded. The duration of the workshops varied between 1.5-3.5 hours and the project group constituted the workshop participants. The three design inquiries were documented in three ways by the first author: (1) Interview and observations were conducted by the members of the project group (design inquiry 1), (2) photos of the emerging Data Sphere were taken and ad-hoc interviews with members of IU who created and contributed with data source ideas (design inquiry 2), and (3) interviews with the members of the project group and emails from external stakeholders were gathered. This study is based on Workshop 4 and 5, which comprises 6,5 hours of video material, 12 photos documenting the development of the Data Sphere, and three interviews with members of the project group during the process of executing the Data Experiments. Our thematic analysis focused on how the members of the project group selected certain data source ideas through joint discussions, their subsequent design of Data Experiments, and their execution of these Data Experiments.

## 4 TWO DESIGN TOOLS AND RELATED DESIGN ACTIVITIES

Subject to the analysis presented in this article are two specific design tools and the related design activities. To facilitate the understanding of the thematic analysis presented below we will now describe the tools in detail.

### 4.1 The first design tool: The Data Sphere

The Data Sphere tool aims to prompt domain experts to generate ideas for new (use of) data sources. The notion of sphere refers to a space over or within which someone or something exists or has influence [37].

People and organizations are existing and navigating in an increasingly connected world as a result of the growing use and implementation of digital technologies and data [26, 32, 39]. Therefore, it could be argued that data to a varying degree influence an organization's sphere. The first author developed the Data Sphere to explore how an organization and its members can engage with this increasingly influential space of data.

Figure 2 shows how the Data Sphere is made up of a wall poster (3,5*3 meter) with a mapping at its centre. The mapping was, in this case, developed by the project group during workshop 2. The mapping depicts human actors (colleagues, stakeholders, organizations, businesses, etc.) and non-human actors (technologies and data sources) that an education consultant interacts within their everyday work life. The purpose of placing the mapping at the centre was to situate and spark creativity for the development of ideas for data sources that may improve current (data-related) work practices or support service innovation in the organization. The Data Sphere is represented as the space surrounding the mapping. To populate the Data Sphere, the members of the organization had to fill out one or more copies of a 'data source idea form'. This form included the following factors: *Name of the data source, Where does the data come from?, What kind of data is it?, Why is it an inspirational data source?*.

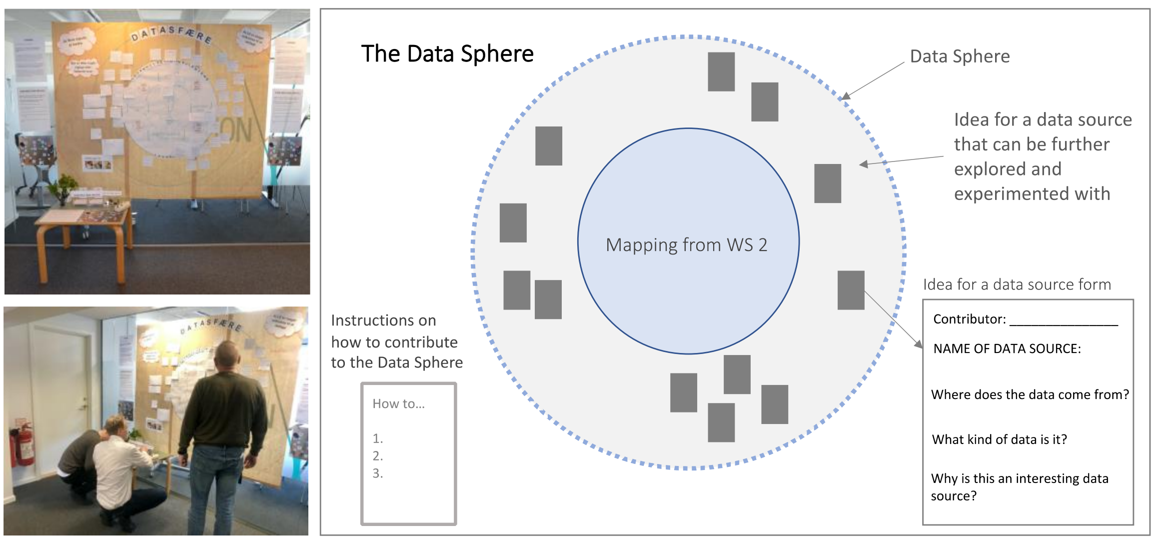


Figure 2: The Data Sphere

The design of the form was intended to prompt the members of the organization to generate 'data source ideas'. Based on previous insights from the action research project, we had learned that it was essential to design tangible and somewhat structured tools in the context of promoting the domain experts to work creatively with data [45, 47]. Management required that the forms should include space for the employee's name because they wanted to get an idea of who participated in the co-design of the Data Sphere.

The Data Sphere was placed the central hallway at IU after workshop 3. The tool was introduced during the monthly information meeting, where all members of IU were invited to contribute with 'data source ideas.' Over the course of one month (May 2019), the members of the organization created 40 different ideas, which they added to the Data Sphere using the data source idea forms.

The co-designed Data Sphere was subsequently processed and evaluated by the project group during workshop 4. This workshop was designed to help the project group selecting data sources for exploration, and on this basis design Data Experiments to explore some of the suggested data source ideas.

During workshop 4, the project group was asked to process these ideas in two rounds: In the first round, the group was asked to examine each of the 40 idea forms and physically move it from the Data Sphere to a whiteboard. The second round focused on idea selection based on weighted parameters [41]. The members of the group were asked to discuss five parameters to identify which of the ideas were useful for further exploration and experimentation. The aim was for the group to prioritize and select four ideas that should constitute the point of departure for the design of Data Experiments. The group decided on: *Quality, Value, Resources, Competences,* and *News Value*. Then, they collectively graded each idea on each parameter from 1-5. The group selected the four data source ideas with the highest score for further exploration and experimentation.

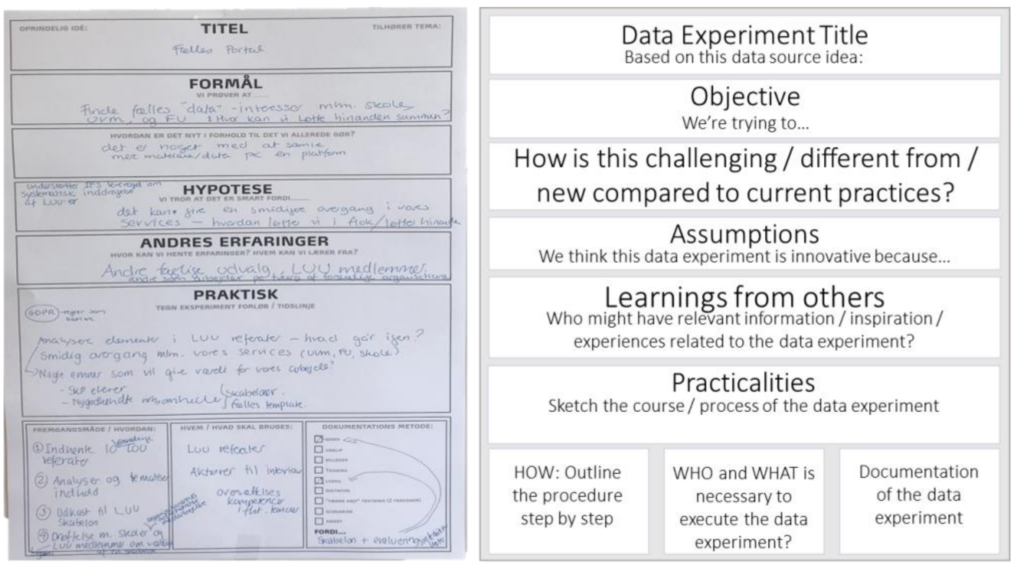


Figure 3: The Data Experiment Template: Example and translation of the template.

### 4.2 The second design tool: The Data Experiment Template

The Data Experiment Template is a tool that aims to support domain experts to explore and experiment with data sources they themselves have identified as potentially useful. Previous insights from the action research project had made visible that the organization had minimal experience with prototyping and testing ideas and concepts [47]. To accommodate this condition, a 'recipe'-like template was developed to support the project group to design concrete 'data experiments' that would enable the project group to explore their selected data sources in ways that would take their limited design capabilities, time, and context into account (see Figure 3).

The project group used the tool in workshop 4, where they designed the four Data Experiments based on the selected 'data source ideas' (see Table 1). Then, the project group executed their data experiments over the course of three weeks ('design inquiry 3', figure1). The project group had managed to carry out two of the four Data Experiment in full. This experimental phase was followed by the project group sharing their experiences and evaluating the tools in workshop 5. We elaborate on the execution and outcomes of the Data Experiments in the analysis below (in particular section 5.5).

Table 1: Overview of the four Data Experiment designed by the project group.

| Experiment | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| Title | Data about Elective Specialization Courses | Colleagues as a data source | Phone interviews for trend spotting | Open Source System for all |
| Data source | Structured, quantitative data | Unstructured qualitative data | Structured qualitative data | semi-structured quantitative and qualitative data |
| Objective | To explore how 1) identify relevant users of this data source and 2) to develop a suitable way to share the data | To explore how colleagues can be considered a valuable data source | To explore how phone interviews can be used to spot trends in Industry in a structured way | To explore and identify common "data interests" with selected external stakeholders to improve cross-organisational data work |
| Newness | Existing data source, exploring new ways of organising the data work | Existing data source, exploring whether/how colleagues can be considered a data source | Existing data source, exploring new ways of organising the data work | New data source |

## 5 ANALYSIS OF THE DESIGN TOOLS AND ACTIVITIES

In this section, we analyze the use and evaluation of our two proposed design tools and their related design activities. First, we examine the implementation and use of the Data Sphere tool. Second, we analyze the group's use of the Data Experiment Template and unfold the two data experiments they carried out.

### 5.1 The Data Sphere: Understanding the organization's data usage

A great benefit from the implementation of the Data Sphere was its ability to create a design space in the organization that prompted discussions related to data usage between managers and employees across divisions and teams. Informal conversations with and observations of people in the hallway showed that the organizational members were happy to be included in the process of generating 'data source ideas' that could be further explored. Moreover, the involvement increased their curiosity about the project. The display of the project group's mapping from workshop 2 also enabled feedback and questioning of this representation. However, the Data Sphere also challenged the organization in the sense that it invoked discussions and reflections about what constitutes as data in the context of various work practices. Thus, the inclusion of the entire organization ensured both generation of ideas from various members of IU, increased awareness about the project, and prompted reflection concerning the data work undertaken in the organization.

Working with the ideas from the Data Sphere also made visible that it is challenging to distinguish between one's personal Data Sphere and the organization's Data Sphere. During workshop 4, the project group processed the Data Sphere by categorizing the 40 data source ideas in three overall clusters: 'Already applied data sources' (20), 'New data sources' (17), and 'Data Attitude Statements' (3). Based on a joint discussion, the group members decided to exclude the "Data Attitude Statements" because it did not include or refer to any particular data source. When discussing how to categorize the data source ideas, a group member expressed their understanding of the difference between one or the other form of Data Sphere: '*We are talking about what constitutes the employee's data sphere, and what constitutes the organization's data sphere. There is much qualitative information that is part of your data sphere; for example, something that we do not have time to document or informal conversations. And then there is the organization's data sphere, which includes what we* *report, and which forms we populate*' (Employee 2, Workshop 4). The need to distinguish between the individual's vs the organization's data sphere is relevant as it illustrates how data work happens at different 'levels' in an organization, and how it is necessary to know what 'level' you are designing for.

### 5.2 Collectively designed parameters are a useful way to select data source ideas

Our design process differs from previous work because it aimed to support organizational members to identify data sources. During workshop 4, the first author made use of 'weighted parameters' [41] as a way to support the project group to assess and select the data source ideas. Thus, the project group had to decide on five parameters, which would constitute the subsequent 'evaluation criteria' of all the ideas. The excerpt below illustrates how the group members negotiated which parameters to include as well as aligning the meaning of each of the parameters (Employee 2 and 3, Workshop 4):

E2: *"I immediately think of 'data quality' [as one of the five parameters]."*

E3: *"Yes, that is a good start. Write that [on the board]. I also think 'Validity' is important."*

E4: *"But I think that [validity] is a subcategory of data quality. Reliability and Validity belong under Data Quality, right?"*

E2: *"Yes, but that also depends on how many parameters we have, oh right five, then yes, I agree."*

We observed how this approach created common ground within the group by prompting them to argue for each of the parameters for each of the ideas. Through these ongoing discussions, the activity supported the group's ability to select data source ideas that suited their skills and context. For example, the discussions on the parameters made it easier for the individual group members to argue why, e.g. 'Data about Elective Specialization Courses' should be graded as a highly valuable data source. This indicates that the activity is useful to support domain experts in the process of evaluating and selecting data sources for further exploration.

Another observation was how this design activity made visible to the project group that their organization is strongly connected with many external stakeholders: If IU changes their data work, it will most likely influence other actors' data practices [45]. When evaluating ideas for the subsequent design of Data Experiments, the project group discussed, for instance, the competencies that it requires to retrieve data about 'Elective Specialization Courses'. The excerpt below illustrates part of this discussion (Employee 2 and 3, Workshop 4):

E3: *"Yes, that is a 1 [very easy to retrieve]! I have been in contact with [employee at the governmental agency for IT and learning], who generates this data. And when I get the data, I can easily make a pivot table [in a spreadsheet] – it is just a matter of a few clicks."*

E2: *"But can we retrieve the data on our own?"*

E3: *"No, we cannot extract the data ourselves because it is from EASY-A [governmental IT system, which is inaccessible for the employees at IU]"*

E2: *"Okay, so we depend on them [contacts at the governmental agency for IT and learning], but that makes things much more complicated."*

This excerpt exemplifies how the project group, again and again, were made aware of the organization's data interdependences with external stakeholders.

Overall, the project group thought the exercise very helpful as a way to process the Data Sphere and structure their discussions regarding the selection of data source ideas. When evaluating the design activity, one participant stated that '*it was fascinating to articulate these different dimensions of data. I wonder if I can use it [the parameters] for other data-related tasks'* (Employee 2, Workshop 4). Thus, our observations from this design activity indicate that collectively selected parameters help to align workshop participants' understanding of whether and why a data source should be selected for further exploration.

### 5.3 The Data Experiment Template reveals the need for tangibility

To work with 'an experimental mindset' is uncharted at IU. Due to this organizational condition the members of the project group had to both comprehend how to explore their selected data sources while simultaneously learning how to prototype, carry out, and evaluate minor experiments with the self-selected data sources. This challenge became visible when the project group were making use of the Data Experiment Template (workshop 4). Here, we noticed that they preferred the template's specific questions while skipping the more open-ended part of the template, which encouraged the participants to sketch the data experiment (see Figure 3). We observed that the rather specific aspects of the template promoted discussions about the scope of the data experiments as well as the contexts in which they would take place. For instance, the template's section on 'Learning from others' opened up for discussions about external stakeholders that may be affected if IU changed the way a particular data source was handled. A similar situation occurred when the project group discussed the 'Practicalities' of the data experiments. This aspect of the template made the group members reflect on how to implement the Data Experiments in ways that took other tasks into account. This observation was confirmed when the group evaluated the Data Experiment Template. They emphasized that they enjoyed the tangible format and the guiding structure, however, they "*did not know how to tackle the drawing exercise*" (Employee 5, workshop 4). Together, these observations suggest that domain experts benefit from rather comprehensive and specific instructions in order to grasp how they can work exploratively and experiment with data.

### 5.4 The abstractness of data creates challenges for design

One concern regarding the exercise of designing Data Experiments was the data source's level of abstraction. We noticed that the data source's level of abstraction influenced the project group's ability to experiment as well as the possibilities for implementing the Data Experiment within the time frame of the project. For example, Experiment 2 revolved around how the organization could consider colleagues as a data source to promote best practices and insights about data work across teams and departments in the organization. One group member explained how the data source's "fluffiness" had challanged their ability to implement the experiments: "*This [experiment 2] did not revolve around a new data source per se but focused on developing a way to better structure an existing data source. This data source idea was abstract, and it made it difficult to make a concrete experiment with it*" (Employee 4, workshop 5). In contrast, Experiment 1, which focused on data about 'Elective Specialization Courses' and revolved around structured, quantitative data had made it easier for the participants to carry it out. This observation suggests that it is relevant to consider a data source's level of abstraction in relation to the domain experts' knowledge of and experience with creating and conducting experiments.

### 5.5 Unfolding two Data Experiments

In the following sections we elaborate on the two Data Experiments carried out by the project group during this study (see experiment 1 and 4 in Table 1). These two Data Experiments exemplifies different ways the project group designed the data experiments and experimented with the self-selected data sources.

### *5.5.1 Data Experiment 1: Quantitative Data about Elective Specialization Courses*

Data Experiment 1 was based on the idea to explore how members of the organization could work differently with a data source that was only being applied to a limited extent at the time of the workshop. The data source constituted structured data about 'Elective Specialization Courses'. These courses are a mandatory part of all vocational educations in Denmark (see [46] for detailed explanation).

The project group decided to explore how this data source could be made more available both for more members in the organization, but also to consider how this data could be shared with organizations similar to IU that could also benefit from making use of the data source. The project group wanted to explore and reflect on the process, in detail, that the consultant (Employee 3) goes through from requesting the data to making use of the data source at a Sector Skills Councils meeting. They also wanted to prototype and test a 'data source guide' that could enable people at IU and in other organizations to explore this data source.

The project group thought it was easy to carry out Data Experiment 1, but they thought it was difficult to document and reflect on their process because "*it was so straight forward"* (Interview with Employee 3, June 2019). The project group created a step-by-step guide which they implemented in the dataset to support other education consultants' and external stakeholders' ability to make use of this data source. After designing this prototype 'data source guide' they shared their experiment with their colleagues at IU and with external stakeholders, who they assumed might find this data source useful. Both colleagues and external stakeholders provided positive feedback, which amongst other things highlighted that the 'data source guide' had made it more accessible for people who were not familiar with this data source.

Another interesting outcome from Data Experiment 1 was the project group's reflection on how this more explorative and experimental way of working with the data source had helped them to establish better the need for this data both within at IU and in external organizations. This particular data source is fragile because IU is dependent on other stakeholders in order to be able to get access to the data, but also because the stakeholder whom they dependent on (in this case a governmental agency) has decided to close the IT system that underpins this data source. However, by establishing and strengthening a joint data need among multiple stakeholders in the larger network, IU may be able to counteract the decision to shut down this data source in the future. This suggests how the connectivity between organizations can be used wittingly to influence the production and usage of data and data structures.

### *5.5.2 Data Experiment 4: An Open-data-source System for All*

Data Experiment 4 aimed to identify common 'data interests' amongst certain stakeholders to further explore whether it might be useful to create a shared cross-organizational system inspired by the open- source idea for software. Compared with Experiment 1 above, this data experiment had a much more abstract point of departure. The idea did not include a specific, structured and quantitative data source. Rather, it constituted a grand vision for cross-organizational data management of multiple and heterogeneous data sources. To develop such an open-data-source system was beyond the scope of this project. The project group were to design a Data Experiment that addressed the issue; however, in a way that would be manageable within the scope of the project and concurrent with their other tasks. The group decided to focus on meeting minutes from Local Education Committees, as a concrete example for an open-data-source. These minutes are an important source of information for IU and many external stakeholders and thus could exemplify a limited 'space' to explore common data interests in a multi-stakeholder environment. The project group designed a data experiment where they analyzed ten meeting minutes and identified themes that could provide a framework for a more generic minutes template that could ideally create a pathway for joint data interests – and data collection.

Findings from their analysis of the meeting minutes showed great inconsistency amongst the ten most recently submitted meeting minutes. Due to this great inconsistency, they decided to prototype a minutes' template, which they assumed could generate valuable insights for the education consultants at IU. Their prototypes constituted an agenda-like list of data categories that they thought would be very useful and insightful in their own work. The categories ranged from broad topics related to "development activities" to more specific aspects such as "discussions on Local Education Development Plans". Subsequently, the project group asked for feedback from three members of different Local Education Committees. They conducted the feedback by sending an email, which included a short explanation about the experiment, the list of suggested data categories, and five questions about their 'meeting minute prototype'. They also followed up with phone interviews.

The feedback from the selected stakeholders varied significantly. Two of the committee members replied that it seemed like an interesting idea but did not think they had a say in a potential development process. The third committee member was in line and stated, "*this is interesting; it's something we can use as a structure"* (Email from Local Education Committee member 1. June 2019). However, this member also chose to share the list and interview questions with his affiliated local vocational college to make sure he did not overstep his role. This resulted in a surprising email to the members of the project group. The email was from a principal at the local college, who was very frustrated about "*having been left out of the decision-making process of this new initiative*" (Email from a principal at a vocational college. June 2019). The project group at IU attempted to solve the situation by emphasizing that the suggestions for data categories in the minutes *only* constituted an experiment. However, the situation escalated, and the project group was contacted by the chairperson of the largest trade union in Denmark, who requested clarification of IU's meeting minutes initiative. This development of a 'simple' Data Experiment shows some of the challenges of changing data practices and co-designing in complex and (data) connected settings [8]. As one of the members from the project group expressed: "*This tells something about the network we are navigating in and how politically sensitive it is, because they perceived it [the prototype] as criticism… I <u>did</u> write that this was just an experiment, I wrote it was just some ideas, but [the principal at the local vocational college] interpreted it as a criticism of their minutes*" (E2, WS 5). Although the project group emphasized their experimental approach and objective, it challenged existing power structures amongst these 'data interdependent stakeholders'. This underlines the value of experimentation when innovating in 'data-driven ways' in a cross-organizational context.

Our findings presented in this section suggests benefits and limitations for how the two proposed design tools support domain experts' identification, exploration and experimentation with self-selected data sources.

## 6 DISCUSSION AND FUTURE DIRECTIONS

In this section, we discuss three key insights which emerged from our analysis of co-designing Data Experiments with domain experts in an organizational context. Finally, we point to directions for future work.

### 6.1 Data exploration makes data interdependence visible for domain experts

Our work suggests that data exploration supported our domain experts' understanding of the interdependence between different stakeholders that manifests itself in the data and its usage. The Data Sphere became a steppingstone for the organization to consider the many low-hanging fruits consisting of potential data sources to probe. As a tool, the Data Sphere prompted the organizations' collective awareness of data as something that can be explored. The parameters that the project group collectively chose to guide their selection of different data sources helped them to understand and articulate the complexity of the suggestions. Particularly, it was the parameters *resources* and *competences* that promoted the group's discussions about how a given data source would also imply considerations for specific stakeholders and their data work. Moreover, the actual implementation of the data experiments made this data interdependence visible to the project group. For example, experiment 1 made the project group aware of the fragility of the data source, because it required other stakeholders (and their IT systems) to get access to the data. This data experiment also showed the group how they could make use of the broader network in order to secure their data needs better. Data experiment 4 made visible that the proposed joint creation of data represents a change in relationships between stakeholders and that domain experts were well aware of the cross-organizational dependencies.

Both experiments point to the need to consider the interaction between different stakeholders, both when designing data and making use of data in a specific context.

### 6.2 Experimenting with data sources promote the value of co-design

The data experiments presented above indicate that in order to develop new ways of data usage and to reap the benefits of specific data and data analysis, the wider context even beyond the organization needs to be considered. This is in line with Degnegaard's [8] argument for creating settings that support co-design amongst stakeholders. In the above reported experimentation with data, the benefit of co-design became visible not only to us researchers but also to the project group. Especially, data experiment 4, which created unforeseen ripple effects forced the project group to respond to the concerns and needs of other external stakeholders. For example, when evaluating the implementation of data experiments, Employee 3 said: '*I've begun to look into the notion of co-design – I mean what is it really? Now I understand that when you collaborate, you create something for the target group, but when you co-design, you develop together with the target group… we need to be open to the possibility that they [other stakeholders] might have a different agenda… I think it is crucial that we cocreate in the future: we need to understand when to throw in the towel and say: we cannot control this, we need to co-design these [data] solutions with others that want to control just as much as we do…*' (Employee 3, workshop 5). Other members of the project group echoed this realization by emphasizing the need to expand the involvement of external stakeholders. It could be argued that the participants benefitted from the overall co-design approach of the longitudinal action research project, and thus was motivated to learn more about this topic. However, we interpret the empirical evidence to suggest that the Data Experiment Template as a tool and the process of exploring data sources and implementing data experiments supported the domain experts' understanding of the data interdependence and thus connectivity between IU and other external organizations. Recognizing the need for co-design in order to reap the benefits of data and analytics points to the need to not only acknowledge that data needs to be designed [15], but to develop a *co*-design perspective on data [43, 44], which is further discussed in the next section.

### 6.3 Cooperative experimentation with data sources exposes data's ambiguity as 'design things'

We think Ehn [14] purposefully leaves the interpretation of 'design things' ambiguous. On the one hand he draws on the Scandinavian tradition, meaning that 'thing' refers to meeting spaces where concerns and political decisions are addressed. On the other hand, he also makes use of a more object-oriented understanding of the concept that refers to '*the object of concern in design, the design object and its many 'representatives', the design of things as matters of concerns and possibilities of experiences'* [14:92].

This ambiguity resonates with our observations. On the one hand, data became an object of design during our process: During the co-design process of IU's Data Sphere both existing and new data sources were collected as design-openings to explore further. In workshop 4, we observed how the domain experts discussed data from different perspectives, and as an entity with many parameters, in order to decide which data sources to choose. Through the use of the Data Experiment Template, data also became a malleable 'design material' as the tool enabled the project group to consider new ways to make use of their selected data sources. On the other hand, the tools and methods to promote the design with data also created a space to discuss and explore data as a common issue. For example, the Data Sphere created a physical space that allowed all members of the organization to gather and to question the status quo by discussing data-related possibilities and constraints. Likewise, the workshops created meeting places where the members of the project group could consider the interconnectedness with other stakeholders through data and discuss ways to address the political sensitivity in this cross-organizational context. Furthermore, through the reactions of the external environment it became very visible that if data experiment 4 was to be implemented, it would require a thorough deliberation and co-design process – with other words: another design thing – to agree on the use of minutes as data.

In another part of the action research project, we explored notations that facilitate the co-design of concrete structures of data [44]. Here, we also observed that the careful choice of notations allowed the joint exploration and discussion of data needs and data. Thus, further exploration of representation, tools, and methods that let data design things emerge, can contribute to address the political dimension of data and data analytics [26, 30].

## 7 CONCLUSION

This study aimed at understanding how domain experts who are not IT professionals, can explore and experiment with data sources they identify and select themselves. We propose two tools, which we term the Data Sphere and the Data Experiment Template. The tools enable domain experts to design and work with data sources in different ways. We identified both benefits and limitations for how our proposed tools affected domain experts' ability to work creatively and design with data. Our design process led to the implementation of two distinct Data Experiments. Both data experiments indicated the need to consider the interaction between different stakeholders when making use of data in a specific context. Moreover, through the experimentation with data sources, the benefit of a co-design approach became visible to the domain experts. Recognizing the need for co-design in order to realize the benefits of data and analytics reveals the need to not only acknowledge that data needs to be designed [15] but also to develop a *co*-design perspective on data [43, 44]. Finally, our cooperative exploration of and experimentation with data makes its ambiguity as 'design things' visible. Thus, this work represents an effort to stimulate future investigations into representation, tools, and methods that can enable the emergence of data design things. With the current focus on how we design (for) data (use), we encourage the design community to join the conversation on how to expand the human centred design approach to enable, facilitate or craft design work that articulate and incorporate data to a greater extend.

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