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Highlights

- Data can be made an object of design in collaborative design workshops
- Making data an explicit element of collaborative design support domain experts who are not IT professionals to work creatively with data
- The physical character of a data notation is important
- Use of multiple data notations are helpful in collaborative design workshops
- Participatory design is a useful approach for foregrounding data

Foregrounding Data in Co-design

– An Exploration of how Data may Become an Object of Design

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Abstract

The rise of Big Data and data science has prompted a focus on data as an essential component of making and innovating data-based services. Traditionally, however, digital data has not been object to co-design as have other physical or functional dimensions of IT application design. This is problematic, because it hinders domain experts who are not IT professionals from taking part in the discussions and design of the data-based services they use and provide. We argue that to address this challenge, it is necessary to empower such domain experts to be able to consider data as an object of design, so they may contribute their expertise to the design of data-based services and their underlying data structures. This paper describes how data may be foregrounded as an explicit element of design that support domain experts' understanding of data as something that can be designed. We present a detailed interaction analysis of video recordings of three collaborative design workshops, in which we propose a form of data notation and two data representations. We find that data may become an object of design for domain experts when tangible and flexible representations of data are used. Based on our findings, we discuss five lessons learned for foregrounding data in co-design. Together, these provide practical insights for future work.

KEYWORDS: Data, Data as input for design, Data as an object of design, Co-design, Participatory Design

1. Introduction

This paper explores how data may be represented through co-design in ways that enable professionals outside the field of computer and data science to make sense of, and critically consider, data and data schemata in design. This focus stems from the growing need to make sense of the ever-increasing availability of data (Russell et al. 2018). Developments such as Big Data and Artificial Intelligence have made it necessary for organizations to become more 'data-driven', in order to utilize and benefit from 'the data economy' (OECD 2019; European Commission 2020). However, employing tools for data aggregation and analytics often requires highly specialized skills and knowledge. This means that core stakeholders and users are excluded from the design discussions that determine what kinds of data are necessary, which existing data sources should be included or excluded, and which data sources should be explored to innovate and design data-based services (Boyd and Crawford 2012; King, Churchill, and Tan 2017). The growing use of digital technologies and data are transforming societies with significant implications for how organizations provide and develop their services (OECD 2019; Bright et al. 2019). The increasing digitalization of services is expected to improve not only the efficiency of service production, but also service quality and service provision in organizations (Sangiorgi and Prendiville 2017; Malmberg 2017). Thus, as data becomes a defining basis for many (digital) services, it becomes more and more important to critically consider the underlying data and data schemata that partly shape these services, which affect our everyday lives to various degree. Therefore, it is necessary to develop pathways that enable domain experts who are not IT professionals to engage with data and data-structure design.

This study addresses the need for tools that can enable domain experts to participate in design with and of data and data-structures. We investigate ways to foreground data in collaborative design situations, which enable domain experts to consider data and data structures as something that may be designed, rather than as a 'given' that only informs the design of a service, for example. Previous research has argued that data is intangible in nature, but that it may be represented in a number of ways, which emphasize different aspects of the data (Kitchin 2014). The way data is represented affects how people make sense of, and engage with it. Therefore, the representation of data frames what we may say, how we may say it, and how we eventually act, based on this (Boyd and Crawford 2012; Gitelman 2013; Kitchin 2014). More recently, these critical perspectives on data have been brought into the design field to demonstrate how the production, collection, and ongoing use of data may also be considered design activities (Feinberg 2017; Speed and Oberlander 2016). This paper builds on the perspective that data is designed, and data collection itself is a design activity (Feinberg 2017). The aim of this paper is to expand this perspective by demonstrating *how* data may become an object of design that enables domain experts to think about data and data schemata in collaborative design situations. Thus, the paper contributes to the emerging body of work that explores how data may become more accessible to a broader audience, to bridge the growing gap between people who can work effectively with data, and people who cannot (D'Ignazio 2017)

This paper is based on a study at a medium-sized service organization based in Copenhagen, Denmark. The main purpose of the organization, Industriens Uddannelser (English: 'The Education Secretariat for Industry', hereafter 'IU'), is to coordinate processes related to maintaining and developing vocational education programmes and courses for continuing education in the industrial sector. IU exists in and navigates a large network of stakeholders in order to provide its core services. As part of a larger, ongoing project, this study focuses on the redesign of an existing data-based service, which revolved around an existing IT system and its one connected database. This paper builds primarily on three collaborative design workshops from the initial stage of this redesign process. We do so by presenting a study in which we analyse interactions among various stakeholders (employees and managers from various small and medium-sized organizations) during three collaborative design workshops. During these collaborative workshops we also explored various ways of making data a more explicit part of the design process. We draw on the established field of participatory design (PD), which is understood as a design discipline that aims for direct user participation in design processes (Kensing and Blomberg 1998). Moreover, we use and adapt representations from service design, to guide the design of the services related to the existing IT system. Therefore, we understand co-design in a broad sense that refers to a general concept for collaboration surrounding design, involving a number of people (Zamenopoulos and Alexiou 2018).

The paper proceeds as follows. In section 2 we present our related work by questioning why it is relevant to foreground data in design, what it means to design with data, and how to create paths to foregrounding data in design. In section 3, we describe our research setting. This is followed by section 4, where we elaborate on our methodology, the three collaborative design workshops, and our analysis of the empirical material. In section 5, we present our three main findings. (1) Our proposed data notation makes it possible for the domain experts involved to discuss data and to establish a mutual understanding about the data among several stakeholders. (2) The domain experts are able to distinguish between data and the real-life situation it models through the use of notation. (3) Notation may support domain experts' understanding of data as an object of design. In section 6, we discuss our findings and present five lessons learned from our explorations of ways to foreground data in design. Finally, section 7 presents the conclusion.

2. Related work: Why design *with* data?

This section presents the theoretical foundation for our exploration of how data may become an object of design in collaborative design processes. First, we briefly address previous research that has focused on rethinking the role data plays, and how to represent data in cooperative and participatory design. We refer to this as using data as input for design. Then, we present Feinberg's (2017) design perspective on data, which we use as a lens to examine what it means to design with data. On this basis, we argue it is important to also be able to empower domain experts to consider data as an object of design in some collaborative design situations. Finally, by referring to literature on participatory design and service design, we question how to create paths to making data an object of design for domain experts.

2.1 Why should data be a foregrounded element of design?

We begin by questioning the relevance of foregrounding data in design to position our research in relation to prior work. For thousands of years, mankind has experimented with physical representations as means to make sense of abstract data (Jansen et al. 2015). For example, the Incas of ancient Peru developed a system for transmitting information, which was based on spatial arrays of coloured, knotted cords (Ascher and Ascher 1997). Today, designers and artists increasingly use digital data to express meaning *in* data, as well as to convey messages *through* data, for instance, by creating data sculptures and digital artworks (Zhao and Moere 2008; C. Jordan 2009). In research, several strands of work aim to better understand how to meaningfully visualize and represent data and information. For example, Information Visualization and Data Physicalization have developed as research areas that examine how to make appropriate conversions from digital data to human-readable, and even tangible representations (Jansen et al. 2015; Dove and Jones 2014b; Goodwin et al. 2013). In the context of design, researchers have argued for the relevance and usefulness of (big) data in Human Computer Interaction (HCI) research and user interface design, while emphasizing the subjective character of data collection and cleaning (Boyd and Crawford 2011; Fisher et al. 2012). Previous studies have explored how Information Visualization may be used in the front end of design projects as tools that make quantitative data more accessible and engaging for workshop participants (Dove and Jones 2014b; Dove 2015). Others have examined how designers may incorporate a data science practices in their design process (Kun, Mulder, and Kortuem 2018; Kun et al. 2019). Importantly, HCI research has begun to identify the creation of data as design activity per se (Feinberg et al. 2017; Feinberg 2017). Generally, this prior work suggests and demonstrates the relevance of representing data in design to a greater extent, because it can help a broader audience to consider and engage with ‘the data’ that underpins more and more of the IT services we use every day.

Another reason for making data an explicit object of IT design lies in a critical perspective on data, which has developed in the fields of Science and Technology Studies (STS) and Computer Supported Cooperative Work (CSCW), raising the awareness of data as constructed, fundamentally contextual, and interpretive (Gitelman 2013, Ribes 2013). These critical perspectives emphasize that data-production is not a neutral act (Rosenberg 2013;

Markham 2013; Kitchin and Lauriault 2018). On the contrary, every decision made about data before the data is collected supports the possibility of certain types of actions, while simultaneously restricting others (Sanches and Brown 2018). Decisions about what should and should not be measured, and which aspects of the data should be made visible, are choices that affect the social world to various extents, and therefore should not be underestimated (Churchill 2012; Ribes and Jackson 2013; Gray, Gerlitz, and Bounegru 2018). These decisions result in the schemata that describe the structure of the data that underpins the computation and interaction. For example, Sanches and Brown (2018, 3) state that *even before data is inscribed in databases, the work of producing data can have profound effects in the social world.* Other researchers have addressed this topic by proposing the concept of Human-Data Interaction, exploring the role of data in Smart Cities, examining how accountability is established through the use of IoT data, and proposing a research agenda for Human-Centred Data Science (Crabtree and Mortier 2015; McMillan et al. 2016; Fischer et al. 2017; Aragon et al. 2016). As such, critical perspectives on data emphasize that one should not take data and data schemata for granted. Rather, it is important to recognise that the production and framing of data is influenced by preceding decisions and assumptions. By being more aware of this condition, data and data structures can be explored differently in design (Feinberg 2017).

This section sheds light on two important reasons that data should be a foregrounded element of design. Our review of previous research shows that there is a growing body of work that indicates the need to make data and data structures visible in ways that enable people to critically consider data in a design context, and to actually design with data (Dove 2015; Dove and Jones 2014b; Speed and Oberlander 2016; Kun, Mulder, and Kortuem 2018). However, previous research primarily reports on exploration of design with data when data is used as *input for design*. For example, Dove and Jones (2014b) included energy data in a service design workshop that aimed to *generate ideas for a new service that utilise data generated by smart meters* (p. 283). They report how the workshop participants were introduced to data that *represented seven days' energy use for one household, based on a selection of possible consumption patterns rather than particular demographic factors* (Dove and Jones 2014b, 283). Thus, in this case the focus is on the design of the service, not on the design of the data used for the service. In other words, in this case data is used as input to inform the service design, rather than to consider data and its schemata as an integrated part of the service design. This exemplifies how so far, research has primarily explored data as something that may inform the design process (data as input for design), for example, of a digital service. These efforts are valuable steps towards foregrounding data in design. However, to consider data and its schemata as an integrated part of design practices, we argue it is also necessary to realize whether a given method can also expose *data as an object of design*: data as something that may be itself be designed. To develop this discussion, we present Feinberg's (2017) design perspective on data in the next section.

2.2 What constitutes a design perspective on data?

We apply Feinberg's (2017) design perspective on data as a lens to examine the question of what it means to design with data in a collaborative design context. Feinberg (2017) emphasizes data as a core component of today's information technologies, and points out that it is important to consider data and its schemata as an integrated part of the design. Feinberg (2017) proposes considering '*data collection as a multi-layered set of interlocking design activities*', and argues that the subsequent use of data is a continuation of these activities. This perspective emphasizes that from the initial decisions of choosing what to measure and how as well as what not to measure may be viewed as design activities (Feinberg 2017). In her work, Feinberg demonstrates that data collection is a result of design decisions, which she divides into three stages: conceptual infrastructure, collection processes, and aggregation processes.

Below, we use Google maps to exemplify Feinberg's perspective on data. Google Maps is a well-known example of a data-based service used in Western societies (Dittrich, Seidelin, and Grönvall 2018). Google Maps constitutes a data infrastructure, where data is not only used to store and retrieve information about specific persons, facts, or situations, but also, the data input itself helps to *create* the service on an ongoing basis. Feinberg argues data infrastructures such as Google Maps generate 'a set of conditions under which design after design can occur' (2017, 2956). In other words, the pre-set values (e.g. how you describe an address) are 'data decisions' that generate Google Maps as a service, and constitute an infrastructure through which data is created and collected. Moreover, this data infrastructure is continuously improved – or 'redesigned' by the users, who use the service by describing their wishes/needs (e.g. to find a certain location) through attributes that are controlled by the 'data decisions'. Feinberg (2017) refers to the accumulation of these preceding data decisions as the service's *conceptual infrastructure* (from a computer science perspective, they are captured as data schemata). It is through this conceptual infrastructure that ongoing *collection* can occur. Feinberg (2017) emphasizes that the data infrastructures can restrict the ways in which data are collected, which may further constrain the intended use-design of the data. In the context of Google Maps, these collection processes are expressed in the ways the service calculates and times various routes for the individual user. Finally, Feinberg (2017) refers to *aggregation processes*, when describing the accumulating number of acts of independent collection that, combined, can determine an 'outcome' of a data-based service.

For example, this occurs when Google Maps calculates and suggests the fastest or shortest route, depending on the means of transportation and recent traffic information.
Feinberg's (2017) perspective on data has a technical underpinning that may resemble extract–load–transform processes of traditional database programming. Nevertheless, this perspective is different in that it does not take the extraction of data for granted. Overall, Feinberg's (2017) perspective on data sheds a light on the necessity of considering the preceding data decisions that feed into the definition of a data infrastructure (data schemata) that will eventually underpin data-based services.

What may be gathered from Feinberg's (2017) work is that data may constitute an entity that has been designed, created, and exists in the world, and data may also be a flexible object that may be altered during its existence. Thus, her work underlines the importance of considering data a malleable construct that may be designed. In this sense, Feinberg's idea about data design goes beyond the research where data is understood and used as input for design. As an alternative, she proposes rethinking how we design data infrastructures, and suggests a more reflective and/or critical design *of* data.
However, Feinberg's work does not (yet) address how to make data object to design. Traditionally, digital data has not been object to design as have other physical or functional dimensions of IT application design. This is problematic, because it hinders domain experts who are not IT professionals from taking part in the discussions and design of data infrastructures. Therefore, to develop this area of research, this study has explored how data may become an explicit element of design that support diverse domain experts' understanding of data as something that can be design rather than something that is pre-defined. In the next section, we elaborate on our considerations on how to create pathways that can support domain experts' participation in the design of data and data structures.

2.3 How does one create pathways that foreground data as an object of design?

Researchers have called for more data-conscious design that makes it possible to explicitly understand data and data practices in ways that are more attuned to design processes (Churchill 2012; Speed and Oberlander 2016; Feinberg 2017; Kun, Mulder, and Kortuem 2018). Therefore, this section considers how we might foreground data as an element of design that resonates with domain experts, who are not IT-professionals. D'Ignazio proposes the notion of creative data literacy, and suggests that we need to create 'pathways towards data which do not come from technical fields' (D'Ignazio 2017, 7). She emphasizes that data literacy is not simply about acquiring technical skills, but also the emancipation bestowed by literacy. This emphasizes that, for the world to become fairer, it is not enough to teach people how to read a table, for instance. It is necessary to teach people how to use the table (D'Ignazio 2017), and – as we will argue – discuss how the table should look and what kind of data it should be able to capture. The increasing use of data and the continuous growth of the field of data science has generated new opportunities for applying new tools to aggregate, combine, and visualize data (Cao 2017). However, many of these tools require specialized IT skill sets that may act as a barrier, and prevent people and organizations from designing with data. Moreover, the increasing production, collection and aggregation of digital data simultaneously entangles and makes organizations dependent on certain data sources (Seidelin, Grönvall, and Dittrich 2018). This is interesting when we consider how organizations work with data, and more or less explicitly use and collaborate around (the same) data (Seidelin, Grönvall, and Dittrich 2018). This indicates a need to not only foreground data in design, but to foreground it in ways that make sense to multiple stakeholders, and represent 'multiple voices' (Suchman 1993; 2002). On this basis, we propose participatory design as a pathway-generating approach to foregrounding data as an object of design in collaborative design contexts. We elaborate on our proposal in the following subsection.

2.3.1 Participatory design as a pathway-generating approach

Participatory design is a design discipline that aims to elicit direct user participation in project definition and design processes (Kensing and Blomberg 1998; Simonsen and Robertson 2012). This strand of research introduced approaches that involve users in the design process, and aims to develop ways for users to articulate their needs and influence decision-making, in an innovation project, for example (Buur and Larsen 2010). To some extent, participatory design is about facilitating a process where different stakeholders can determine, and articulate their needs, and through that process make the design fit their needs, rather than adjusting their needs to fit the design. Through these objectives, participatory design emphasizes the situated expertise of various stakeholders, and how to establish collaboration among these actors (Buur and Larsen 2010).

Participatory design applies a range of methods and techniques that support engagement and ways to articulate and consider multiple voices in a design process. Collaborative design workshops and methods often involve end-users – whether older adults, children, workers, or people with a specific interest such as bird-watching – in the design of novel interactive modalities and interfaces for interacting with technology (Bossen and Grönvall 2015; Guha et al. 2004; Hiniker, Sobel, and Lee 2017; Still et al. 2004; Lindsay et al. 2012). Many co-design tools take an Interaction Design stance, and are oriented to Interface design, to map out communication flows and to identify key stakeholders in a situation (Bossen and Grönvall

2015; Halse et al. 2010; Kristensen, Kyng, and Palen 2006). Traditional PD methods have addressed data and data schemata indirectly, for example, in interface mock-ups where data is represented through the elements that provide the functionalities to manipulate the data. This means that for participatory design to be a useful pathway that helps to foreground data as an object of design in collaborative design contexts, it is necessary to develop data notation that supports diverse stakeholders in articulating their needs and use of their shared data to guide the design. To do so, we need to both unpack and make tangible the existing data structures, in order to enable domain experts to critique and (re-)design them. To this end, we wanted to explore methods that might enable domain experts to explicitly design with data in a collaborative workshop setting in a particular context. Our design and evaluation of data notation were inspired and guided by Engeström's concept of expansive visibilization (Engeström 1999), which emphasizes the need for representations that establish new design spaces. We describe the notion of expansive visibilization and our use of the concept in the following subsection.

2.3.2 Expansive Visibilization as a tool for evaluating data notation

We adopt the concept of expansive visibilization (Engeström 1999) as an analytical lens for examining the extent to which data representations support domain experts in their critical evaluation of the current situation, and their ability to explore possibilities for change and its design implications. Engeström (1999) introduced the notion of expansive visibilization as a way to conceptualize a representation's capacity to give rise to discussion, questioning, and critical reflection of the status quo. Thus, Engeström (1999) aimed to incorporate a developmental aspect when analysing (primarily) transformation at work. He argued that such activities are often represented in a two-dimensional manner, which he refers to as the linear and socio-spatial dimensions. Engeström (1999) exemplifies the linear dimension of work by referencing Business Process Modelling, which aims to represent the processes of an organization as a temporal series of activities with the purpose of optimizing these processes. This approach often results in a rigorous description. Engeström (1999) emphasizes that linear representations of work are often very limited in terms of generating discussion and allowing people to question the processes. According to Engeström, the socio-spatial dimension goes beyond the linear dimension of representation. The socio-spatial dimension refers to a way of representing work that encounters discourse and situated actions with and without artefacts, for example. This dimension challenges the linear representations by including a greater level of complexity, and by taking into account how processes are actually enacted collaboratively in time and space. Engeström (1999) emphasizes that the socio-spatial dimension fails to uncover how processes and their transformations come about. Therefore, Engeström (1999) proposes a third, developmental dimension that aims to frame the linear and socio-spatial dimensions in a broader perspective, to expand representation of work, and in this way support people's discussion of, and critical reflection on, work activities. On this basis, we apply the notion of expansive visibilization as a lens to characterize and evaluate ways of foregrounding data in design. Specifically, we use the concept to consider how and in which way(s) data representations create opportunities for design.

2.4 Summary of related work

The research presented in this section suggests that data may be, and is used as input to inform collaborative design processes (Dove and Jones 2014b; 2014a; Dove 2015; Kun, Mulder, and Kortuem 2018). However, owing to organizations' increasing dependence on various data sources, the related work also reveals a need to foreground data in ways that allow multiple stakeholders to *co-design data*. Applying Feinberg's (2017) design perspective on data, we emphasize that data may constitute two 'things'; it may be an entity that has been designed, and an entity that may be designed. We argue that it is important to be sensitive to this, to understand how different forms of notation support design with or of data, either as input for design or as an object of design. This sensitivity is essential when designing data-based services used by a number of stakeholders in different contexts and with different data-related practices, because the design of such a service implies data design. As a first step in exploring how this may be done, we adopted a participatory design approach, to build on traditional co-design methods, in order to explore how notation may support domain experts' understanding of data as an object of design. We also propose using the concept of expansive visibilization as an analytical tool to characterize and evaluate the applied notation.

3. Research setting and research focus

This section presents the research setting in which our study took place, and elaborates on the emergence of the research focus. The research was carried out at Industriens Uddannelser (English: Education secretariat for industry, hereafter the acronym IU is used), which is an education secretariat based in Copenhagen, Denmark. IU develops and ensures the quality of vocational education and adult vocational training programmes in the industrial sector. IU is a main driver for ensuring the continuous development and upgrading of the qualifications of Danish industry (IU 2019). Thus, maintaining and developing these educational programmes constitutes IU's core services. In doing this, IU navigates a highly complex network of stakeholders, including ministries, governmental agencies, trade unions, employer associations, vocational colleges, various councils and committees, and other education secretariats. To navigate and eventually provide its services in this complex setting, IU is dependent on heterogeneous data sources, and therefore data is at the core of the internal work, and when IU engages in its many collaborative activities with external stakeholders. What constitutes data in this context varies. A few examples include quantitative data on students participating in vocational education (number of students in a specific course, grades, number of apprenticeship), relevant reports and analyses produced by government agencies and think tanks, and qualitative interviews with management and employees working in industrial enterprises.

This study originated in the examination of the work and cross-organizational collaborations required to maintain the data in a single database, and the redesign of an existing information system that supports the management of this particular database (Seidelin, Grönvall, and Dittrich 2018). In this case, IU collaborated with multiple stakeholders to facilitate the service provision of the data on the individual members of the more than 160 Local Education Committees (LECs). To understand why LECs exist and the role of these governing bodies, it is necessary to elaborate on the broader context of the vocational educational system in Denmark. The Danish labour market is based and builds on tripartite negotiations among the social partners of the labour market (the government, employers' associations, and unions). Among other things, this negotiation affects and regulates the vocational education system and the adult vocational training system. IU was established to facilitate the ongoing collaboration between the social partners, to ensure the maintenance and development of vocational education programmes, specifically for the industrial sector in Denmark. Furthermore, each vocational education programme is controlled by a Skill Sector Council that consists of representatives from unions and employers' associations. Together with the Danish Ministry of Education, these Skill Sector Councils determine the educational framework. Finally, these frameworks are locally implemented through governing bodies known as LECs, which are affiliated with specific vocational colleges. Generally, an LEC consists of four to eight members, including representatives from the vocational college, and relevant employer associations and unions. The LEC members include a student and a teacher from the local college, and representatives from the unions and employers' associations. The representatives from the employer association(s) and union(s) are appointed by the union or employer association with which they are affiliated, and usually work in some local industry. IU provides services to maintain this setup by managing and communicating all relevant data about each LEC member, as needed (findings from our study on data maintenance in this cross-organizational context appeared in Seidelin, Grönvall, and Dittrich 2018). This data work requires many supporting manual processes, which often result in 'data discrepancies' among IU's three main stakeholders, each of which depends on this data. Therefore, in collaboration with the key stakeholders, IU decided to launch a redesign of the LEC database and its related IT system. To support this development, we proposed three collaborative design workshops, which included a data notation that specifically represented the entities in the current LEC database's schemata, and several other forms of adapted service design notation intended to support the initial steps of designing a new IT system that can manage this cross-organizational work. In the next section, we present our methodology, elaborate on our workshop activities, and describe the applied notation to further analyse how these support design with data.

4. Methods

The research presented here is a part of a larger, ongoing three-year action research project involving the IT University of Copenhagen and IU. The action research project focuses on how domain experts (who are not IT professionals) in organizations can take part in the design of data and data structures that underpin the services used by and influencing the work practices of these same domain experts and the network of stakeholders with which they are collaborating. We understand action research as a methodology, which means that the research aims to induce change and improvement of certain aspects of a targeted research domain (Robson 2002; Stringer 2013). In this case, IU constitutes the research domain. This paper builds on the first of three interventions, and thus presents the initial phase of the action research project. The objective of the first action research intervention was three-fold: 1) to understand what constitutes data in the context of IU, and examine how people use and make sense of data, 2) to introduce collaborative design methods at IU as a new approach to collaboration that supports innovation, and 3) to explore ways to foreground data in collaborative design situations. This project conducted its inquiry through design methods and techniques, as a way to induce change. In line with Binder and Brandt (2017), we argue that not all design practices are research practices, as research practices must respond to a research question or concern beyond, such as the (design) brief of a project. Thus, this project applies Research-through-design (Frayling 1993) as an intervention process (Zimmerman, Stolterman, and Forlizzi 2010; Koskinen et al. 2013).

4.1 Data collection

We collected data from March 2017 to January 2018 (figure 1). During this period, the first author spent approximately 3 days a week at IU. We decided, in collaboration with the management at IU, to focus our action research intervention on the LEC database because it appeared to be the simplest and most "isolated" area of IU's IT infrastructure. The first author identified key stakeholders related to the LEC data work together with employees and managers at IU. Then, we “followed the data” (Leonelli 2016; Bates, Lin, and Goodale 2016) by first conducting 20 hours of field observation that encompassed 15 semi-structured interviews with administrative ‘data workers’, who made use of, and contributed to the maintenance of the LEC data. Together, they represented 12 different organizations (including education secretariats, employer and employee associations, vocational colleges, and IU’s external IT provider). The observation and interviews focused on the practices that go into producing, collecting, applying, maintaining, and updating the LEC data across organizational boundaries. By exploring the production and use of LEC data, we developed a comprehensive understanding of current data practices at IU and the cross-organizational work, including collaborative data practices that are necessary for maintaining the database. The initial data collection also revealed the key stakeholders’ very limited knowledge about how the LEC data was produced, maintained, and used in other organizational contexts (Seidelin, Grönvall, and Dittrich 2018). Therefore, we suggested designing and facilitating three collaborative workshops that aimed to support the redesign of the LEC database in a way that put the domain experts at the centre of the development work. We also aimed to establish mutual understanding amongst these key stakeholders. Finally, we wanted to use this opportunity to explore how data can become object to design in a collaborative design context. On this basis, the workshops were designed to explore in various ways how data may become an object of design. Each of the three workshops lasted approximately 2.5 hours, and all were documented as video recordings, images and workshop materials. In the following subsections, we elaborate in greater detail on the design of the workshops, and the workshop participants.

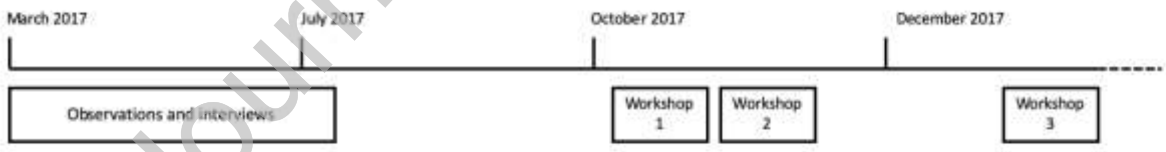
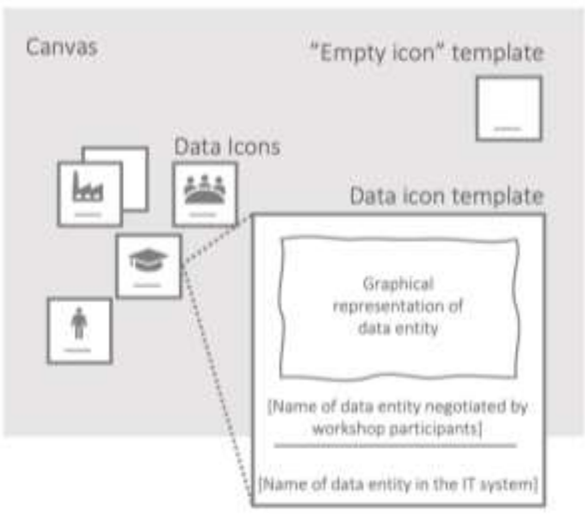


Figure 1. Timeline for the data collection.

4.1.1 The first workshop

The first participatory design workshop involved six participants, one facilitator (the first author) and one observer (the second author). The workshop had two general objectives. The first goal was member checking (Robson 2002), by verifying our initial analysis of the empirical material (observations and interviews) with the workshop participants, the administrative workers that were responsible for LEC-related tasks at IU, two unions and an employer association, which are the four key stakeholders in this case. The second goal was to explore notation for explicitly foregrounding data in a collaborative design context. The notation consisted of a set of simple graphic icons that represented the data entities in the current LEC database (see figure 2 below). We also included “empty icons” to allow the participants to create their own, e.g. if they felt a data entity was missing (figure 2). We chose to represent the data entities as icons, in an attempt to enhance the participants’ data literacy in a non-technical manner. This is in line with previous studies that called for ways to foreground data so it supports learning and creative work (D’Ignazio 2017; Wolff et al. 2016). Examples of data entities are Schools, Education Programmes, and Education Consultants (which were represented as a building, a graduation cap, and the outline of three people, see Figures 2 and 3). To some, our notation may appear to be a physical, movable Entity-Relationship Diagram, a structural model that is often used in database design as a way to visualize relationships amongst the data entities in one or more databases (Ramakrishnan and Gehrke 2003). Therefore, it is important to emphasize that our notation is not to be confused with an entity-relationship diagram. First, the aim of our notation was not to produce a data model, but to support the workshop participants’ understanding of data and database design as something that influences their work practices, and vice versa. Furthermore, the aim of our notation was to make visible to the participants how various stakeholders made use of data in similar and/or different ways, and in this way show how their underlying information and data needs determine the data schema that constitutes the service provision framework of the LECs. As such, our notation may be considered a useful tool and design activity when used prior to developing an Entity Relationship data model.

We experimented with the notation by using it in two different ways. First, we included in activities where the participants could relate to the notation on a blank canvas. Then, we used the data notation in a more structured format. To provide a structured format, we developed a matrix to prompt the participants to critically question aspects such as who generates the LEC data, how data is shared amongst various actors, and who uses the LEC data. This matrix constituted a 2×2-metre poster with a grid that emphasized stakeholders and activities. We refer to this structured format as the Data Matrix. In the next section, we explain the workshop activities and our use of the data notation.



Figures 2. and 3. On the left: A generic remake of the canvas, data icons and “empty icons”. On the right: The workshop participants are negotiating the meaning of the data notation and their relationships. The data notation employs a blank canvas and a set of tangible data icons.

The workshop was designed as follows. First, we presented the insights we had collected from the field observation and interviews, in which all the participants had participated, and we invited them to comment on and discuss these (for a more in-depth description of the findings, please see Seidelin, Grönvall, and Dittrich 2018). On this basis, the first author introduced the notion of a database, and explained that the structure of a database depends on the data one needs, emphasizing that a database, and by extension, the data schema, may be altered and organized according to these needs. The workshop participants (apart from the participating authors) had very limited knowledge of IT systems and databases, despite their regular maintenance of the LEC database, and thus this perspective on IT and data was new to them. In the second phase of the workshop the participants were introduced to our data notation. The participants were asked to discuss the notation, to establish a shared understanding of what the various icons represented. This activity was carried out on the blank canvas (see figures 2 and 3). Then, they were asked to remove and/or add data entities (using “empty icons”), if they agreed that there were either redundant or missing entities. Finally, they were asked to discuss how they thought the data entities were related. This was intended to prompt discussion on the participants’ joint and varied data needs and practices. In the third phase of the workshop, the participants were asked to place the data notation on the data matrix (see figures 4 and 5). In this way, we observed how a more structured format influenced the workshop participants’ ability to talk about data. The workshops’ final phase and activity was a feedback session, where the participants were asked to reflect on the workshop, their experience with the data notation, and the implications of the two different formats (blank canvas and data matrix).

DATA MATRIX Activities / Stakeholders	Industriens Uddannelser	Key unions and employer associations	LEC Member	Vocational Colleges	Additional stakeholders?
Data generation					
Sharing of data					
“Data approval”					
Use data					
Delete/edit data					
Additional data activities?					

Figures 4. and 5. At the left: a translated version of the Data Matrix.

4.1.2 The second workshop

The second participatory workshop followed shortly after the first workshop. The purpose of the second workshop was also two-fold. First, it aimed to build on the insights from the first workshop, in order to generate ideas for the redesign of the LEC data and related IT system. Simultaneously, we wanted to examine whether foregrounding data in the first workshop would affect the ways in which the participants generated ideas. This workshop consisted of the same six domain experts, and three additional participants: one representative from the main employer's association, one administrative worker from a vocational college, and one LEC member. Again, the first author was the moderator and the second author observed the workshop. This workshop was inspired by the 'Future Workshop' technique (Jungk and Müllert 1987), which is well-established in the PD community, because we wanted the participants to focus on identifying specific problems with the current situation, and to explore how to address these concerns.

The second workshop revolved around two design activities. The workshop started with an introduction of the participants, as additional participants had joined the second workshop. The first author also summarized the activities and discussions from the first workshop. The first design activity involved 'the critique phase', where the participants were asked to critique the current handling of LEC data and the related IT system. This was followed by a general discussion in which the participants shared the points of their critiques, which they subsequently categorised. We used this categorization as the basis for launching the second design activity, which was the 'visionary phase' in which the participants were asked to design visions of new and improved ways to manage and collaborate with and through the LEC data and IT system. To document this phase, we introduced the participants to Storyboarding (Tassi 2009), a method used in design processes to visualize concepts. The participants were unfamiliar with method, but nonetheless attempted to draw storyboards of their visions in pairs (see figure 6 for an example). This was followed by presentations of the storyboards and ideas. The final phase of the workshop was a feedback session, in which the participants were invited to reflect on their experiences and the use of tools for idea generation.

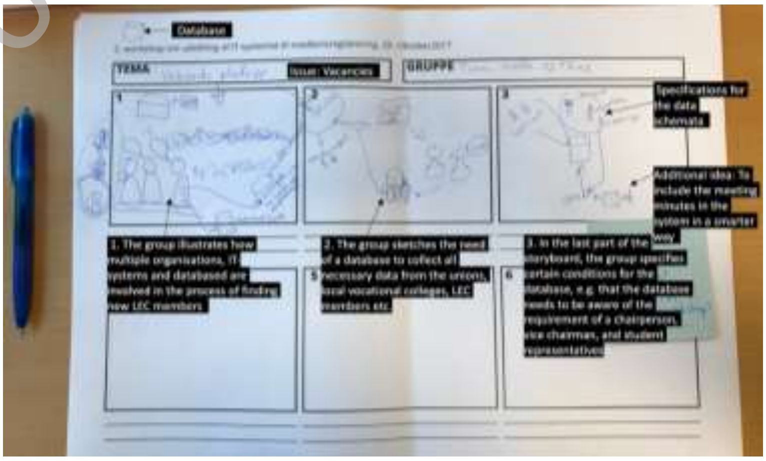


Figure 6. An example of a storyboard.

4.1.3 The third workshop

The third workshop differed from the previous two in that it involved only employees from various departments at IU. Thus, the workshop participants were three administrative employees, three managers, and one facilitator (the first author). This workshop aimed to bring together the insights and collected ideas, to create a foundation for the future development of a redesign of the LEC database and IT system. Moreover, we wanted to explore additional ways to foreground data at a slightly later stage of the design process. To do so, we complemented our participatory design approach with notation from service design (Blomberg and Darrah 2015), to also keep IU's service focus an explicit part of the design process. At its core, service design is about the process and act of designing services (Kimbell 2011). Service design draws on many disciplines (including participatory design), and may be understood as a design specialization, as it specifies a specific design focus. The emergent field of service design has developed tools and techniques that motivate a holistic perspective when designing and innovating a service and its context (Ostrom et al. 2015). We understand services as socio-material constellations that provide a functionality useful to a third party. Service design notation has been developed to support the design of these socio-material constellations (Blomberg and Darrah 2015). We chose to use two forms of service design notation. The first is known as the *service ecology map*, which is a tool used to map collaboration between service actors and stakeholders, in order to investigate the relationships amongst these parties (Polaine, Lovlie, and Reason 2013). Traditionally, this tool focuses primarily on human and nonhuman actors, which may include forms of technology used to support these relations (e.g. a computer or a phone). We wanted to explore whether a service ecology map could be incorporated to foreground data and to observe how it would play out in a collaborative design context. On this basis, we designed a 'service ecology map toolkit' that consisted of a canvas with a circular pattern, and octagonal icons in various colours to represent the following categories: 'Organization', 'Individual', 'Technology', 'Data Source', 'Questions' (to account for questions that might occur in the design situation), and 'New Ideas' (to facilitate the possibility of idea generation in the design situation). Although we initially identified central actors in collaboration with management and employees at IU, we chose to explore this tool as a means to 're-open' the design process and make room for new, additional actors relevant to the redesign of the LEC database.

The second notation we included in the third workshop is called the *service blueprint,* which is a tool that helps to visualize various service components (e.g. people, tools, and processes) and how they are linked throughout the service journey (Lynn Shostack 1982; Shostack 1984; Bitner, Ostrom, and Morgan 2008). A service blueprint is a matrix that allows users to identify each step of a service journey, and then visualize how each step affects service components above or below ‘the line of visibility’, which refers to the element that the user can or cannot see or experience while going through this process. In line with our inclusion of service ecology maps, we also wanted to examine how data could be foregrounded when using a service blueprint in a collaborative design situation (figure 7). Therefore, we altered the service blueprint to include two additional aspects below the line of visibility. We termed these aspects ‘Necessary data’ and ‘New potential data sources’. The aim was to observe whether this alteration of the notation would prompt the participants’ consideration of data that is needed to support the various steps of the data-based service and service provision, and to stimulate a consideration of data that could be explored in order to determine whether it could add value to the future service.

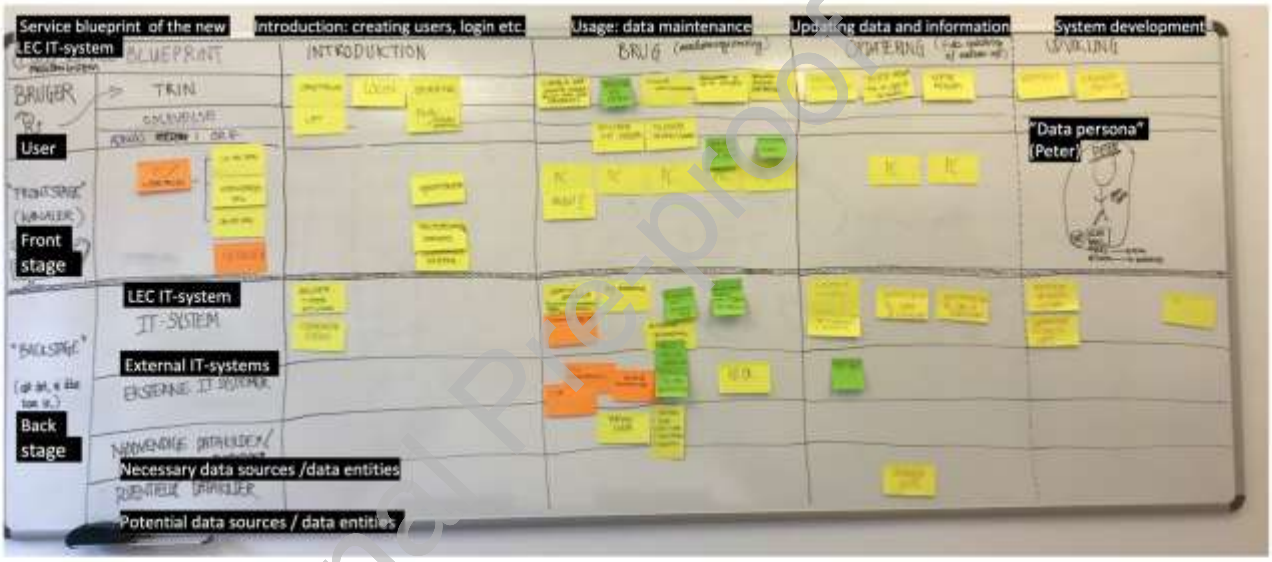


Figure 7. Extended service blueprint.

The workshop was designed as follows. First, the participants were divided into two groups, each of which got a ‘service ecology map toolkit’. Then, one group was asked to create a service ecology map from the perspective of an administrative worker at IU, and the other group was asked to create a service ecology map that put an administrative worker from an external organization at the centre of the map. This was followed by a joint discussion and comparison of the two service ecologies. Building on the mapping exercise, the next design activity revolved around the development of a service blueprint to support the redesign of the LEC database. We chose to make a ‘sketchy’ template for the service blueprint, to give the impression that it was not the final design. We did so by simply drawing the blueprint on a whiteboard, and asking the participants to collectively add Post-it notes with suggestions for the various stages and aspects of the service journey. We chose to include the service blueprint as a means to articulate and encapsulate the insights concerning the subsequent process of negotiating and collaborating with external IT developers in commencing the technical development of a redesigned LEC database and IT system. As we did in the first and second workshops, we concluded the third workshop with a feedback session in which the participants were asked to question and comment on the activities, and share their experiences.

4.1.4 Summary of the data collection

This article builds on a data collection consisting of field observation, semi-structured interviews, and three collaborative design workshops. The initial observations and interviews formed the basis for the three subsequent workshops. The general goal of the collaborative design workshops was to explore how various forms of notation facilitate explicit data design in collaborative design situations, and also to understand how such notation influences domain experts' ability to design with data. Despite the general goal of the workshops, each workshop had different objectives, and involved different forms of notation and activities (see table 1). In this article, we focus on the materials (video recordings, images and workshop materials) generated by the workshops. In the following section, we elaborate on our analysis, and how this led to our three main findings.

<table>
<tr><th colspan="2">Workshop 1</th><th colspan="2">Workshop 2</th><th colspan="2">Workshop 3</th></tr>
<tr><th colspan="6">General objectives</th></tr>
<tr><td colspan="2">(1) To verify initial analysis of field observations and interviews with workshop participants, and
(2) to explore our proposed notation for representing data in a collaborative design context.</td><td colspan="2">(1) To build on the insights from Workshop 1, and
(2) to examine whether the foregrounding of data in Workshop 1 would affect the subsequent design process.</td><td colspan="2">(1) To bring together the insights and collected ideas collected in Workshops 1 and 2, and
(2) to explore other ways of foregrounding data at a later stage of the design process.</td></tr>
<tr><th colspan="6">Number of participants</th></tr>
<tr><td colspan="2">6</td><td colspan="2">9</td><td colspan="2">6</td></tr>
<tr><th colspan="6">Workshop activities and design tools used</th></tr>
<tr><td>Activity</td><td>Tool</td><td>Activity</td><td>Tool</td><td>Activity</td><td>Tool</td></tr>
<tr><td>Introduction</td><td></td><td>Introduction</td><td></td><td>Introduction</td><td></td></tr>
<tr><td>Zooming in: Data exploration</td><td>Data notation</td><td>The Critique Phase</td><td>Clustering of brainstorming results</td><td>Combining user perspectives and data practices</td><td>Service Ecology Maps with a focus on technology and data</td></tr>
<tr><td>Zooming out: the context of the data</td><td>Data matrix</td><td>The Visionary Phase</td><td>Storyboards</td><td>Initiating the development of a service concept</td><td>Extended Service Blueprint</td></tr>
<tr><td>Feedback and wrap-up</td><td></td><td>Feedback and wrap-up</td><td></td><td>Feedback and wrap-up</td><td></td></tr>
</table>

Table 1. Overview of the workshops, their main objectives and applied tools

4.2 Analysis

We chose to conduct a close interaction analysis (B. Jordan and Henderson 1995; Plonka et al. 2015) of the video recordings of the three workshops, in order to understand the interactions amongst the workshop participants when they worked with the various forms of notation. Our analysis unfolded as follows. The first author viewed all the video material with two questions in mind: ‘when do people talk about data?’ and ‘how do they talk about data?’. Along with the initial analysis of the video material, the first author also reviewed the workshop output (e.g. the storyboards and images of the service blueprint). This step resulted in a selection of 54 video excerpts, each of which lasted between 17 seconds and 3 minutes. These excerpts were then categorized by the first author, which yielded 14 themes: current data practices, new data practices, data needs, data negotiation, data representation, imagining the future IT system, division of work, transparency, data priorities, real world relations, data relations, simplicity, complexity, and functionality. Bearing in mind that we were exploring how different forms of notation might support various aspects of designing with data (data as input for design, data as object of design, or both) and in light of the foregoing categories, the first author selected 10 video excerpts that best illustrated the 14 themes. These 10 video excerpts, including the participants’ verbal and non-verbal interactions, were transcribed in detail. These transcriptions were later used in a workshop, where the three authors repeatedly viewed the selected video excerpts and read the transcripts. Based on this process, the authors analysed in detail how, for example, the workshop participants during the first workshop related the proposed data notation on the canvas to the data underpinning their common tasks. Our discussions of the observed and analysed interactions led to an understanding of two prerequisites that are necessary for domain experts to be able to consider data an object of design in a collaborative design context. First, domain experts need to be able to talk about data as data, meaning, for example, that they must recognize that they are talking about entities in a database. Domain experts also need to be able to distinguish between the data and the concrete situations it models. This enables the domain experts to collectively be aware of whether they are designing ‘the service situation’, for example, the user’s interaction with a system, or whether they are designing the data schemata that underpin the service situation. Based on our empirical material, these prerequisites seem essential to domain experts’ ability to consider data an object of design in a collaborative design situation. We consolidated this understanding in two steps. The first author reviewed all the video material to ensure that the excerpts were representative of the participants’ discussions, critical considerations, and interactions. This led to the suggestion to include three additional excerpts. Therefore, we held another joint viewing of the three new excerpts. However, this discussion led to an agreement to stick to the selection of the 10 original video excerpts, as the three proposed video excerpts did not illustrate our understanding of the prerequisites more clearly. On this basis, we describe our three main findings, as follows. (1) The concrete data notation makes it possible for domain experts to talk about data, to further establish mutual understanding about the data among multiple stakeholders. (2) The domain experts are able to use the notation to distinguish between data and the real-life situation it models. (3) Notation may support domain experts' understanding of data as an object of design. In this article, we use 6 of the 10 selected video excerpts, as they best illustrate our findings. We indicate duration and which workshops each of these 6 video excerpts came from in our analysis in section 5. In the next subsection, we describe our efforts to ensure the reliability of the research. This is followed by a presentation of our three main findings in section 5.

4.3 Reliability

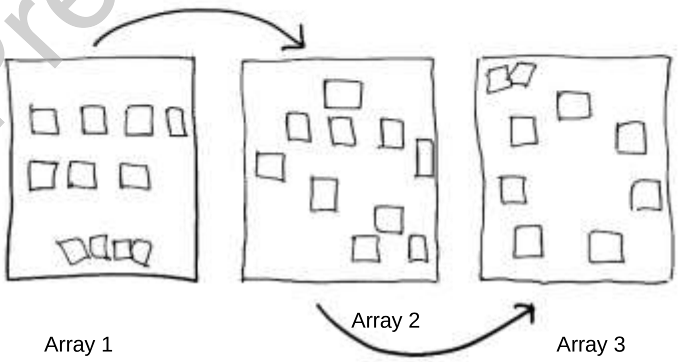
Our study ensured the reliability of our qualitative research (Robson 2002) in four principal ways. First, the fieldwork was carefully documented: interviews were audio recorded and transcribed, and participatory observation and workshops were video recorded. This generated an (1) audit trail and enabled thick descriptions, which enhanced the transparency of the field material and our findings. This also enables the reader to review our findings and insights. Secondly, (2) we triangulated in two ways. We triangulated data points, for instance, our initial participatory observations and interviews, with the participants' statements during the workshops. The first author collected photos, screen dumps, video and audio recordings, and documents, which are independent data points for triangulation. Furthermore, the fieldwork that forms the basis of earlier work presented by Seidelin, Grönvall, and Dittrich (2018), and this article, involved close collaboration among the authors, who compared the transcripts of the video excerpts with the video-recorded material, to ensure that the written excerpts reflected the recording. All three authors participated in (3) debriefing sessions, both following the initial research phase (interviews and participatory observations) and after each workshop, which supported the reflection on, and direction of the research. These debriefing sessions also influenced the first author's selection of the 10 video excerpts. Finally, (4) member checking was used as a technique to improve the accuracy and credibility of our study (Robson 2002). The interviewees, observed individuals, and workshop participants were invited to comment on the developing themes after each phase of the data collection. During the workshops, the participants were asked to evaluate the various forms of notation. This ongoing member checking helped to ensure that the participants' perceptions of the explorations were reflected in our findings (Robson 2002).

5. Findings

This section presents our three main findings. First, we elaborate on our proposed data notation: how it supported the workshop participants discussion of the data in the LEC database, and how it enabled them to explore the existing data schemata and their shortcomings. Second, we show how the data notation helped the domain experts to establish the difference and relationship between data and the concrete situation it models. Finally, we show how data may become an object of design for domain experts in a collaborative design situation.

5.1 Concrete data notation makes data discussable for domain experts

The first finding of our study focuses on how our proposed data notation supported the domain experts' ability to discuss the 'LEC data'. The data notation enabled the domain experts to explore the existing data and its shortcomings. Using data icons to conceptualize the data and to discuss the data through the notation was a first step towards the participants jointly transforming the data into an object of design. In this section, we elaborate on a situation that arose in the first workshop, where the domain experts worked to collaboratively to make sense of the data notation.



Figures 8. and 9. The image on the left shows how the workshop participants tried to make sense of the data notation by positioning the icons in different ways. The sketch (remake of the first author's note from the workshop) on the right shows the various formations the participants used: linear, hierarchical, circular.

The situation arose at the beginning of the workshop, when the participants were asked to talk about their understanding of the data icons and their position on the blank canvas. As mentioned, we chose to represent the existing data entities in the LEC database as simple graphic icons, and experiment with two different notation formats (a blank canvas and the data matrix). The data icons were labelled with the name of the data entity the icon represented (this was the same name that was used in the IT system). During the discussion of their understanding of the data notation, the domain experts placed the icons in various arrays on the blank canvas. The participants initially arranged the data icons in two separate rows, to overview of the individual icons and their relationships. This arrangement changed as the participants began to discuss the relevance, hierarchy, and priorities of the data icons. The configuration of the data icons transformed into a triangular array (see figures 8 and 9). Excerpt 1, below, illustrates how this process of group prioritization was initiated, and how it led to a shared understanding of the meaning of the data notation.

Excerpt 1. Understanding the data notation. (Workshop 1: 00.36.19 – 00.38.53 min.)

Speaker	**Discussion**
Admin-X	The question is – what is the smartest thing to do? Is it to start with this one or that one? *Admin-X leans over the table and points to two icons of the canvas. The first icon is the 'LEC committee icon', the second is the 'LEC member' icon.*
Admin-Z	Yes… what should be the focus? I mean for me… I would always search for the committee [on IU's website] as a first step.
Admin-Æ	I do that, too. *Admin-X takes the committee icon and puts it in the middle of the canvas.*
IU-1	… and then we use that [the LEC committee icon] as a starting point and take it from there? *The other participants agree and nod.* Okay.
IU-2	And then we could put the member [LEC member icon] there, right? *The rest of the group agrees. Admin-Æ moves the LEC member icon beside the committee icon.*
Admin-Æ	And also, which school it [the LEC committee] is affiliated with, right? Like that? *Admin-Æ takes the school icon and put it close to the LEC committee icon. The group agrees.*
IU-2	Do you also look at which skills an LEC member has? *IU-2 points to the skill icon…*
Admin-Z	That skill [icon] and education [icon]… is that the same? *Admin-Z points to the icons.*
IU-2	No, I think 'education' covers areas of education that the committee addresses, whereas…
Admin-Z	The specialty? *Admin-Z looks at IU-2*
IU-2	That's how I understand it *The other participants nod and agree. Admin-Æ moves the 'Education' icon*
Admin-Æ	Then it [the education icon] needs to go here.
Admin-X	But that is important… but is it the same?
Author 2	The 'skill' [icon] is attached to the committee. *Admin-X takes the 'Education' icon.*
Admin-X	Ah, then we could say that this [the education icon] relates to the education at the school [vocational college].

Excerpt 1 comes from the initial phase of the first workshop. The excerpt illustrates in detail the use of data icons on a blank canvas to reconstruct the existing data set and its organization from the domain expert's point of view. The participants started by establishing their understanding of the data icons as stand-ins for the data, and decided how to begin the activity. They decided to use their own interaction with the system as the starting point. Initially, spatial proximity was established as indicating 'is related to' (see figure 9, array 1). The meaning of the notation and the meanings of the individual icons was (re-) established through discussion and by pointing to icons, holding them up, and moving them closer to each other. By pointing to and moving the data notation, they illustrated the data entities they were discussing with the other workshop participants. Thus, the participants also established a shared understanding of their practices, for example, when Admin X says, ‘I would always search for…’.

The situation (Excerpt 1) showed how the participants used the icons to represent the data that the existing system administrates. Through these discussions, the domain experts also agreed that the triangular array of the data did not represent their understanding of the importance and connections among the various data entities. This led to a circular arrangement of the data notation (figure 9, array 3), which became the basis for the participants’ subsequent discussion about the stakeholders’ varying data needs. To guide this discussion, the participants were asked to draw lines on the canvas between the icons, using different colours to represent the relations between the various data entities, according to the various stakeholders’ use of the LEC data. Although this array and these visible relationships may seem final, they did not stop ongoing discussions and negotiations, for example, about how the LEC data is prioritized differently by the stakeholders involved, and what it meant for the future redesign of the LEC database. Instead, these discussions continued throughout the three workshops.

The use of our proposed data notation also revealed that the tangibility of the data icons, and the flexibility of their placement appeared to be important characteristics of the notation. Specifically, they allowed the participants to explore connections and relations. We observed that drawing explicit connections on the canvas took longer. The participants stated that they found this form of activity more permanent. We also observed this aspect when the domain experts experimented with the data notation using the Data Matrix (a more structured format compared to the blank canvas) restricted the domain experts’ ability to explore the relations among the various data entities, and to identify the stakeholders’ varying data needs. This observation was supported by the participants when evaluating the design activities, and specifically, how they perceived the difference between the blank canvas and the data matrix. One of the workshop participants stated, ‘*I think it was difficult to start with a blank canvas, because then everything* <u>*is*</u> *possible, but it was interesting to discuss on such an open basis. Maybe that is also why – when we switched to the Data Matrix – I found it quite restrictive. However, I think the Data Matrix made it very visible to me that IU is at the centre of this. Just look at it: the majority of the icons are in IU’s column*’ (Admin-X, Workshop 1). Figure 5 demonstrates how the workshop participants populated the Data Matrix.

To summarize, our findings indicate that carefully designed data notation supports domain experts' ability to talk about data in ways that enabled them to collaboratively explore connections and relations among data entities. Our analysis also indicates that it is important to consider how expansive a data notation is in relation to the notation's intended aim and use.

5.2. Notation supports domain experts' ability to distinguish between data and the real-world situation it models

Our second finding focuses on the need for domain experts engaged in collaborative design to be able to distinguish between 'a real-world situation' and the data about the situation. Our domain experts needed to understand data as a purposeful representation of specific aspects of the real-world situation, to consider data and schemata as objects of design. In this section, we present two situations that show how the use of notation supports domain experts' ability to differentiate between data and 'reality', to negotiate the meaning of data.

The first situation we discuss comes from the first workshop, where the domain experts discussed whether the proposed data icons reflected the data they used when performing tasks related to maintaining the LEC IT system. Specifically, Excerpt 2 presents the participants' discussion of the meaning of an icon that represented the entity, 'Vacancies'. The participants discuss the difference between data and the situation it models through the use of the notation, by addressing both the larger question of filling vacancies in the LECs (reality), and the need for registered data that can help to solve the question at hand. Thus, the example illustrates how including the data notation in this particular collaborative design situation prompted the participants to critically consider what data is necessary to support their work practices and information needs.

Excerpt 2. Distinguishing between the data in the existing system and reality.
(Workshop 1: 01.22.44 – 01.23.15 min.)

Speaker	Discussion
Admin-X	This is also interesting. I know it is annoying, but we all encounter this issue [refer to the 'vacancies' icon]. *Admin-X leans in over the table and takes the icon of the canvas. She shows the icons the group and puts it aside.*
IU-1	But you need that to have that data [vacancies in the LECs] registered right?
Admin-X	Yes! We think it is important that it is registered, but at the moment it doesn't show, it [the existing LEC system] just say 'vacancy' right? *The group nods and agrees*
Admin-Y	Exactly
Admin-X	Really, there are many more things [aspects] than this [the data icons] *Admin-X indicates it goes beyond the represented data entities. The participants nod.*

Excerpt 2 presents one of the occasions when the participants negotiated what was currently part of the data, and what additional information was needed to take action based on the data. The icon 'vacancy' is referred to as indicating a problematic situation. To resolve it, the administrators refer to knowledge about how LECs have to be assembled: a new member must be nominated or supported by a specific labour market organization. In the excerpt, Admin-X notes the inclusion of this constraint in the redesign of the system: 'We think it is important that it is registered, but at the moment it doesn't show, it [the existing LEC system] just says 'vacancy' right?' In the last round, Admin-X asks, at a more general level, which aspects of the situation should be modelled by the data. This question came up several times in the workshops, as the participants repeatedly discussed and negotiated the meaning of the data icons. When the participants used the data notation, it became clear that they understood data itself as an entity, and that the data model only reflected certain aspects that were relevant to their practices. Excerpt 2 shows how the participants discuss data as an independent part of an IT system.

The second situation we consider comes from the third workshop, where the participants had been asked to populate the incorporated service blueprint. As described in the methods section, we adapted this well-known service design notation to stimulate the domain experts to consider data when consolidating their insights from the first and second workshops into an initial description of future service provision related to the LEC IT system. Excerpt 3 shows a discussion in which the participants tried to establish "the boundaries of the future LEC IT system", as a way to understand what data is necessary to support the redesigned service concept.

Excerpt 3. People distinguish between data and reality: Peter and data about Peter.
(Workshop 3: 02.07.06 – 02.08.53 min.)

Speaker	**Discussion**
IU-3	…then we may as well consider 'where are we missing examiners?', 'which exams are being called for?' or… *IU-3 makes hands gestures to illustrate the various areas that a new system could support.*
IU-4	No! Because that is not what the system should handle. We are registering persons in here [in the system], because you are not going to use it… or then we need to expand this workshop, if we also need to consider how to handle and manage the call for apprenticeship tests… *IU-4 points her pen at the service blueprint.*
IU-3	But examiners are registered, right?
IU-4	Yes, but what I imagine… can I try to draw it, then we can erase it afterwards? *IU-4 grabs a pen and draws a stick figure.* If we imagine Peter. He is an LEC member, a member of [committee], then he is also an inspector [who approves whether or not a company is allowed to train and thus educate trainees] … and then he is an examiner. I don't think there are more things he can take part in… *IU-4 writes Peter's affiliations* We handle this data in [system A]. This [data] is handled in [system B], and this [part of the data] is handled in [system C] … It would be nice if it was just one system… But his master data [personal data] should be here in The System, for lack of a better name. *The other participants repeat 'The System'.* Yes, so when we sign in and 'tick' his affiliations, then The System should recognize, 'ok this person is an examiner', this data is then sent to [system A], so [IU-employee] can access, for instance, a dashboard and then on this basis decide what types of examiners are needed, and see 'I got Peter'. [The IU-employee] doesn't have to think about updating data about Peter, because it's been updated in The System. This is how I envision The System – data-structure-wise – would support our practices. *IU-4 points her pen at the rest of the blueprint. The other participants nod.*

Excerpt 3 presents how some of the participants spoke about the future LEC IT system, in terms of the tasks the existing system supports, and which tasks the future system might support. The participants in the third workshop consisted entirely of IU members. This created a space, where the participants could discuss the data practices that were specifically related to maintenance of the LEC data. However, it also enabled the participants to discuss additional tasks that were peripheral to the LEC data work and currently supported by other internal IT systems. Specifically, IU-3 and IU-4 questioned how and where the data about a specific person with various roles should be stored in the future LEC database. IU-4 emphasizes a typical example of an experienced master craftsman who is a member of a specific LEC, acts as an examiner, and is a contact person for the practical education of apprentices in his company. They propose redesigning the data across various systems, and inventing a new one, 'The System'. This discussion about the boundaries of the future system created some confusion in the group, regarding which service(s) they aimed to improve and/or design. To resolve this uncertainty, IU-4 invented new notation that allows a representation of the various contexts in which the base data is used. The notation describes a 'data persona', a stick figure named Peter, with additional data attributes that represent how 'Peter' should be modelled in the system. IU-4 explained her idea, referring to the data persona and the common understanding of the work practices at the organization. This helped the group to jointly distinguish between the tasks that the LEC IT system can and should support, and the specific data that is needed to model the situation (see Excerpt 3, and figures 10 and 11).

Figure 10. IU-4 explains her drawing of Peter; what constitutes the person and the data about the person.

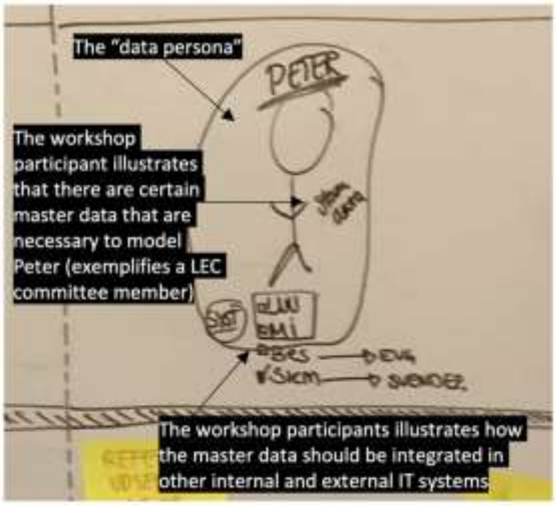


Figure 11. The 'data persona', Peter, drawn by IU-4.

In this section, we presented in detail two situations that in various ways show how notation, which aims to make data an explicit part of design, may support domain experts' ability to distinguish between the data and the real-world situation it models. This is an important finding, because the ability to distinguish between the two is a prerequisite for understanding data as an object of design.

5.3 Data may be an object of design for domain experts

This section presents three additional situations that suggest that data may become an object of design for domain experts in a collaborative design situation. Our third and final finding focuses on how the various forms of notation we used during the three workshops supported the participants' understanding of data as an object of design to varying degrees.

The first situation addressed in this section emphasizes yet another discussion that emerged during the first workshop when the participants were discussing whether there were redundant or missing data icons. Already by this point in the process, the participants began to think and talk about data as an object of design, as they started to discuss improvements to the existing system and data schema. The use of the proposed data notation prompted the participants to question that data schema. Excerpt 4 below emphasizes a discussion during the first workshop, where the participants considered whether certain data was missing from the existing IT system. Here, an IU employee questioned whether 'company' notation was not needed to support one organization's need to know in where their LEC members were employed/employers. This need was confirmed by the representative of the organization, and the data entity was added to the canvas (see Excerpt 4 below).

Excerpt 4. Data as something that may be designed

(Workshop 1: 01.23.45 – 01.25.00 min.)	
Speaker	**Discussion**
IU-1	… and for you [Administrative worker], I am thinking, a piece is missing – one that is called 'company', because it depends on whether the company is a member [of the association], right?…
Admin-Z	Yes, yes it does. *The IU employee grabs a blank icon template and creates a company icon, which she then hands to the administrative worker… Admin-3 adds the company icon to the blank canvas.*
Admin-X	… Then there also needs to be a 'vacancies' [icon], right?
Admin-Æ	Exactly.
IU-1	Exactly.
Admin-X	… It's a question of how you build it [the system] in a data-technical manner. If you know there need to be 3 [LEC members] from [organization 1] and 3 [LEC members] from [organization 2], or whatever… and then there needs to be – because it's not only our own representatives… there are also the schools and sometimes the student representatives, which could be added when it [the system] is constructed… So, there will be many more things than this… *Admin-X points and makes a circular movement with her pen to stress that she is referring to the icons on the table.*

Excerpt 4 illustrates how the data notation enabled the participants to critically evaluate the proposed data icons, in order to identify missing or redundant aspects of the existing data schema. Excerpt 2 already showed that the participants started to propose extensions of the model. Excerpt 4 is more explicit: IU-1 prompted the discussion referring to the constraints on manning LEC committees. To preserve the members' pre-negotiated parity, the company appointing a member representing the employers' side in the LEC needed to be a member of a specific trade organization. This led to further discussion of the details of how to model 'vacancies', as they are not simply the absence of members, but places that need to be filled by persons who fulfil specific requirements. This time, IU-1 raised the question of how far they should go with their redesign. The option to 'debug' the existing data model, for example, by adding a new data icon, enabled the participants to identify what kinds of data were missing from the existing system, and thus extend the data model with new objects (data entities). This indicates that the notation enabled the participants to consider data an object of design, and thus allowed them to design with data, so it could support the improved system functionality.

The second situation that we want to emphasize in this section supports the observation that the data notation supported the domain experts to consider data as an object of design. The second situation highlights how the domain experts in the first workshop discussed the limitations of the existing system. As shown in Excerpt 5 below, the participants note that the existing system is restricted to registering a certain category of LEC member, that is, members that have been appointed by the unions or employer associations. This has led IU employees to creatively (mis-)use the IT system to register additional members whose contact information may be useful for IU and other stakeholders at some point.

Excerpt 5. Creative misuse of the existing system. (Workshop 1: 01.31.12 – 01.33.30 min.)

Speaker	Discussion
IU-2	Well, we have never registered the representatives of the schools [vocational colleges].
Admin-X	No? *The IU employee grabs a blank icon template and creates a company icon, which she then hands to the administrative worker… Admin-3 adds the company icon to the canvas.*
IU-1	No, because – to say it frankly – it would be a nightmare. They [the schools] never tell us anything. *IU-2 looks at IU-1.*
Admin-X	Right
IU-2	Then [IU-1] would have to spend all her time getting in contact with the schools to ask whether there were any updates [to the data]… *IU-1 nods.* … which happens all the time.
IU-1	Yes, we only register them [school representatives] if they contact us, and then we register them as *the school* [in the system].

In Excerpt 5, the participants refer to a limitation of the existing system. So far, only LEC representatives appointed by the social partners have been registered systematically. However, for a number of reasons, it is important for IU to collect the contact information of the representatives of vocational colleges, when it is available. For example, this information may be useful for employees at IU, to serve representatives from unions and employer associations who request updated information about who, from a given vocational college, is affiliated with a particular LEC. As the existing system does not support this functionality, IU employees have registered the vocational college as a labour market organization in the LEC database, so the LEC system can show which representatives from a vocational college are associated with the LEC in question. These practices of creative misuse (excerpt 5) became visible to the domain experts when using the data icons and relating it to the use of the data. They were treated as indications of the limitations of the existing system. This suggests that our carefully designed data notation supported the domain experts in this particular collaborative design situation in transforming data into an object of design, which further enabled the design of additional system features through the data.

The third situation illustrates how the domain experts' experience with the data notation in the first workshop allowed them to more systematically relate to the data underpinning the new service in the second workshop. We introduced storyboards to prompt the participants to discuss and formulate initial service concepts that addressed the points of criticism that had been identified and categorized during the first phase of the second workshop. Excerpt 6, below, presents a situation where a group of participants, consisting of representatives from three different organizations, presents their service concepts by showing their storyboards to the other groups. Their idea addresses 'the vacancy problem', which refers to the challenge of recruiting new LEC members. This is a great challenge for the whole network of stakeholders, as it is required by law that all LECs have a certain number of representatives, and that each LEC has equal representation.

Excerpt 6: Redesign of the LEC database; finding potential new LEC members (Workshop 2: 01.46.08 – 01.47.10 min.)	
Speaker	**Discussion**
Admin-X	We chose to take the perspective of [employer association], because we [the various organizations working with LEC data] have different needs. We thought when [employer association] needs to appoint a new LEC member, they need a database similar to [existing database], with data about approved apprenticeships… *Admin-X points to her group's storyboard* … we talked about the necessity of a [new] database with approved training places… and then you need to be able to search by postal code, so you can look for approved companies in the local area. And then you can look and see if there are companies in the local area. *The representatives from the employer association nod.* … and then we discussed – now I move to the next field…. *Admin-X points with her pen to her group's storyboard to illustrate that she moves from one part of the story the next.* … then, if you consider a [new LEC] database; what needs to be in it for this to happen? It should contain and register LEC members, who is the chairman, who is the vice chairman, who is student representative, and meeting notes. *Admin-X makes hand gestures to show that she is counting the database attributes. The participants nod.* …
IU-2	Can I ask a question? Is it then supposed to be the vocational colleges that register this data? *The participants look at IU-2*
Admin-X	No, the schools should extract [the data]. *Admin-X points to the storyboard again.*
IU-2	Okay.
IU-1	So maybe it needs to be similar to when we extract data from [governmental agency], and then there should be a web service that enables us to say, 'here we need to show X [geographical] area'. *The representative from the employer association nods. IU-1 grabs a Post-it note and starts to write.*

In Excerpt 6 the participants shared their ideas on how to solve one of the key problems: 'the vacancy problem' was already raised during the first workshop (excerpts 2 and 4), and was discussed again during the second workshop. Admin-X explained the storyboard developed by her subgroup. They proposed a 'new database' which should register companies with approved apprenticeship positions, because a company that has apprentices at a specific vocational college is more likely to be interested in the quality of the theoretical side of the education. The group suggested the new database should allow administrative workers across organizations to search for companies based on their postal code. This data entity (postal codes) would indicate the proximity from a company to local vocational colleges to which LECs belongs. Thus, they might be able to identify potential LEC members and in this way address the high number of vacancies in LECs. Furthermore, Admin-X explained that her working group proposed extending the existing data model so representatives from the vocational colleges that are part of a LEC may also be registered, without a workaround. Thus, during the presentations of the storyboards, it became evident that the participants (including Admin-X), who had worked with the data notation and their relationships, applied the negotiated meaning of data from the first workshop to further develop and substantiate their proposals for improving the LEC database (in contrast to those who did not participate in the first workshop).

5.4 Summarizing the findings

Overall, our findings show that data may be represented in collaborative design situations in ways that enable domain experts to regard data as an object of design. This indicates that domain experts can take an active part in designing data-based services' technical infrastructure. The way the domain experts referred to data icons is an example of this. Our excerpts also show how foregrounding data enabled the domain experts to distinguish between data and the situation it represents, and to distinguish between, and connect the functionality of the future IT systems and the data underpinning it. The analysis above also shows that developing this ability to distinguish is not easy. Repeatedly, the domain experts discussed the relation between the data, their work practices surrounding it, and the situation is helps to administrate. These discussions led to an understanding of the role of data underpinning the new IT system's functionality. Multiple representations helped the participants to distinguish and connect the various aspects. The series of workshops with their various related forms of notation for focusing on and connecting services, the functionality of the IT system, and design, supported the participants' ability to consider data as a design object. Our participants, without prior knowledge of database management and data attributes, became more 'data-aware' by applying data representations during the collaborative design workshops. This indicates that the use of relevant notation may help to better connect people who work effectively with data, and domain experts outside the field of computer science and data science (D'Ignazio 2017).

6. Discussion

We opened this article by asking why it is relevant to foreground data as an essential component of making and innovating data-based services. We presented related work that addressed why data should be foregrounded in design, what it means to design with data, and how to create paths to *co*-design with data. We explored participatory design in a service design framework as one approach to create such a path. Then, we elaborated on our interaction analysis of three collaborative design workshops, and presented the results of the analysis of our explorations with various forms of notation, each intended to make data an explicit part of the design process. Our study demonstrates how various forms of notation can mediate between design and data, and how data *can* become an object of design for domain experts in a collaborative design context. In line with Feinberg (2017), we challenge the understanding that data is simply input to design. Instead, we argue that data is designed – both when its structure is determined and when the structure is applied to collect data. We propose that domain experts should also be able to engage in the design of the data structures that underpin the data-based services these same domain experts use in and across organizational boundaries. For these domain experts, who are not IT professionals, to be able to this, we argue that data should also be an object of design during the process of co-designing data-based services. In the following sections, we discuss five lessons learned from our exploration of ways data may be foregrounded in a collaborative design context. We also address the limitations of this work. Taken together, we hope that the insights from this study will inform future investigations into how to support domain experts to co-design with data.

6.1 The data notation is an expansive representation

The first lesson learned from our exploration of how data may be foregrounded as an object of design for domain experts participating in collaborative design situations focuses on our proposed data notation. Specifically, it discusses how our proposed data notation supported the domain experts' discussions and critical reflections that created opportunities for design. The tangibility of the data icons allowed the participants to 'prototype' the mapping of existing and new data. The data icons were specifically designed notation that aimed to reflect the existing data model in the LEC database. The concreteness of the icons made it easier for the workshop participants to discuss which data was essential, less relevant or currently missing. In the workshop setting, the data icons were lifted, moved, pointed at, and placed side by side, while discussing their relation to the participants' tasks and to each other. The icons and the canvas provided a deictic space, allowing the participants to develop a common language about the data by pointing to and moving icons around when discussing their data needs and usage. The participants were able to use the data notation to visualise and discuss how the domain experts had different data needs. Using Engeström's (1999) notion of expansive visibilization, we may say that the notation helped to anchor the discussion and the reformulation of the socio-spatial arrangements of the provision of the related services. Rather than limiting the possibility for discussion and development, this data notation allowed the participants to articulate their needs and question the present data design in this specific design situation. Even though the data notation represented the data entities of the LEC database (visualized through graphic icons) in a relatively linear manner, the way in which the data representation was introduced and used enabled the participants to critically evaluate and expand the existing data model. The possibility of being able to move the icons about on the canvas prompted exploration, for instance, when the participants made different arrays of the data icons, and additional icons were included. Excerpt 4 exemplified how the participants not only constructed the data, they also expressed how they understood the connection between a given kind of data and the functionality. In other words, data was not included and applied as a 'given', but as something that may be altered, based on shared decision-making. Also, the inclusion of 'blank icons' invited the participants to create additional icons, and thus expand the data model. We also observed how, when changing the framing of the notation (from the blank canvas to the data matrix) it prompted a different use of the notation. Although the data matrix had a more structured format, compared to the blank canvas, it supported the participants critical appraisal of the existing situation, in terms of how data is produced, maintained, and shared among actors in a specific context. It is important to emphasize that the case-specific preparation of the data icons involved allowed the domain experts in our study to relate the abstract notation to their reality, without limiting them to the status quo. For other cases, the representations, such as the data icons, would have to be adapted, to allow the domain experts to design with data in their specific contexts.

Our research indicates that it is possible to develop expansive representations that enable domain experts to relate to data as a design object; to critically evaluate the existing data schemata and the processes surrounding their maintenance, and to propose improvements to the data schemata. Being able to make sense of, and think critically about data is important, as it is used as an element that shapes the digital services that have come to play a significant role in how we experience everyday things, innovate at organizations, and structure society. Thus, such representations are essential to supporting people's ability to work with data as an object of design, and to allow for questioning and supporting the development of innovative ideas.

6.2. Data is a difficult design element to incorporate in co-design

The second lesson learned from our study underlines that data is a difficult design element. As we showed in the findings section, it may be difficult to distinguish between what constitutes a concrete situation, and the data concerning the situation (see excerpt 5). Our explorations with various forms of notation indicate that it is necessary to consider the interplay between abstract data and concrete situations, for domain experts to be able to design with data. This is in line with the related work, where, for instance, Dove (2015) argues '*designing interfaces that visualise domain-relevant data with an intentionally ambiguous visual encoding appears to have a negative impact on co-designers' sensemaking, and reduces the appropriateness of their subsequent design ideas*' (p. 278). Although not intentional, the challenge of ambiguous visual encoding also became apparent when the workshop participants used the data icons. We had produced one set of icons, which represented the data entities in the existing system's interface. This resulted in situations where the participants were uncertain whether they were referring to an actor in the network (e.g. a person) or the data about the actor (e.g. the person's name, listed in the database). In the discussion, the participants managed to establish and agree on the relation between data (schemata) and the concrete situation.

Our study indicates that, although data is a difficult design element to incorporate to collaborative design situations, domain experts are able to design both the ‘functionality level’ and the ‘data level’ of the data-based services. This suggests that in collaborative design situations, the need to distinguish between data and the concrete situation it models should be reflected in data notation.

6.3 Using multiple forms of notation may help to foreground data in co-design

The third lesson learned from our explorative work addresses the use of multiple data representations and their complementarity throughout the design process. Although several insights were extracted from the work with the data icons, this notation did not stand alone. The participants were also prompted to consider data when using storyboards, and developing service ecology maps and a service blueprint (Shostack 1984; Bitner, Ostrom, and Morgan 2008). The adapted service ecology map helped the workshop participants to get an overview and identify the different needs of a potential user from IU, and a potential external user of the future LEC IT system. This was a useful way to remind the domain experts about varying data needs, as the third workshop included only members from IU. The expanded service design blueprint also offered useful notation. We adapted this notation to prompt the participants’ consideration of data, when consolidating an initial redesign of the service provision related to the LEC IT system. Our analysis showed that the expanded service design blueprint helped the domain experts to make sense of how data underpins the service to be designed.

Our analysis suggests that it was helpful to introduce the most concrete notation for the data (data icons) during the initial part of the process. The shared sense-making related to the data, and enhanced understanding of data as an element of design, supported the inclusion of data in the other forms of design notation. The concrete and tangible introduction of data early in the process enabled the participants to bring the data ‘forward’ in the later workshops workshop (excerpt 6). This became apparent when the participants built on their knowledge of the LEC data, and drew databases on their storyboards and articulated what data was necessary to support their innovative service concept.

A limitation of our notation became evident when the participants designed their own notation to explain their design ideas. Even though we included several data representations, other/additional representations could have been included. When working with the expanded service blueprint, it became necessary for the group to augment one form of data notation (the service blueprint, extended with a space to define data sources in the form of data icons) with another ('data persona') (excerpt 3). The use of multiple forms of data notation, each with a different design objective, allowed the participants to address both the data design and how it underpins the service provision (e.g. the combination of data icons and storyboards). Again, this suggests that it is important to consider which notation to use, at which point of the design process, and how one data representation may be complemented by one or more other representations.

6.4 Foregrounding data helps to make the technical infrastructure of data-based services visible in co-design

The fourth lesson learned of our exploration of foregrounding data emphasizes and reiterates our emphasis on the relevance of considering both social *and* technical aspects of the process of designing data-based services. The growing number of digital services emphasizes the importance of considering and representing the technical infrastructures (data and data infrastructures and their interconnectedness) that underlie the ways in which we are able to provide and use services. Thus, the technical infrastructure of a service also constitutes essential parts of the context in which the service exists (or will exist). Our study revolves around the process of redesigning a database and its related IT system, which is maintained and provided by collaboration across many different organizations in a large network (Seidelin, Grönvall, and Dittrich 2018). Our analysis reveals that this form of service innovation does not simply influence the social aspects of how people interact and collaborate with the data, and how these practices are most likely to change because of the development and implementation of a new IT system. This form of service innovation also influences the technical infrastructure that underpins the data-based service. Our analysis shows that changing data practices in one setting – for example, how data is handled at IU – will affect how external stakeholders are required to work, for example, register and update data, for the service improvement to be successful. Thus, this will influence how data may be integrated with IT systems in external organizations. This illustrates how practices and services and technical infrastructures are interconnected (Blomberg and Darrah 2015). This emphasizes the importance of acknowledging that when we (re-)design data-based services, we are often building on and/or including established IT systems and practices. Therefore, when foregrounding data in co-design, it is important to acknowledge that we are always 'designing from somewhere' (Suchman 2002).

So far, design and engineering disciplines have focused mainly on either technical or social aspects, when developing data-based service (Seidelin, Dittrich, and Grönvall 2017). Building on Feinberg's work (2017), we show how data may become an object of design that enables exploration and innovation in collaborative, participatory workshops. In other words, we show that data, as a key component of the technical infrastructure, may be integrated into collaborative design situations. In this way, foregrounding data in concrete and tangible ways makes the technical infrastructure of data-based services visible for domain experts during the design process. We argue this may be a way to bridge the growing gap between people who can work effectively with data, and people who cannot (D'Ignazio 2017). In this regard, it is also relevant to consider various ways in which data notation may foreground social or technical (or both) aspects. In our related work, we argued that it is important to be to better understand how different forms of data notation support design with or of data (data as input for design and data as object of design, respectively). Based on our review of the related work (Dove 2015; Dove and Jones 2014b), we suggest that design situations where data is used as input for design may encourage a focus on the social aspects of a data-based service, whereas our intent to promote data as an object of design may advance more technical aspects of designing data-based services. However, future work is needed to examine this observation.

6.5 Participatory design is a useful approach for foregrounding data in collaborative design situations

In this final part of the discussion, we reflect on Participatory Design as a potential pathway-generating approach to foregrounding data in design in ways that do not originate from technical fields (D'Ignazio 2017). The increasing production and use of digital data make organizations dependent on certain data sources (Seidelin, Grönvall, and Dittrich 2018). This results in a growing need for multiple stakeholders to be able to make sense of the shared data, in order to design with data in ways that represent 'multiple voices', and thus address various needs and uses. This constitutes a second argument for why we need to unpack, represent, and make the existing data infrastructures tangible, to design with them.

As outlined in the related work, to the best of our knowledge, existing workshop design materials focus mainly on functionality or interaction interfaces. Well-known tools and methods in participatory design have included data in an indirect manner. For instance, the use of mock-ups to design an interface may include the data represented in the interface underpinning the functionality. We argue that by designing the functionalities of a system, the users simultaneously define which data will be represented in the system. The 'data decisions' are normally invisible to the users (Churchill 2012). One might question whether it is necessary to 'trouble' the users with making these underlying structures visible. In our case, an alternative design strategy could be to rely more on data experts, such as database designers, to design systems. However, even if these data experts were to interview the intended users, this would constitute design *for*, rather than *with* the IU personnel. Our ambition was to enable domain experts to be involved in the design of the data and data schemata that underpin the services used by these same domain experts, and in this way give the projected users a voice in the design. Our analysis shows that such involvement does provide the domain experts with new professional skills. Moreover, it also allowed IU to better understand how they work with data across organizations, how their data may be organized, and how it involves their services. Therefore, we argue that data-related decisions embed the prioritization of service needs and ways of provisioning the service. Data decisions become important to consider in cases where people and organizations depend on, and collaborate on data. These insights contribute to knowledge of the organization, and support the data experts. Domain experts and IT professionals need a way to make sense of and co-design with data. Our study compliments the existing participatory design toolbox by proposing notation that foregrounds data, to enable people to explicitly discuss data. Echoing previous research, we note that a participatory design approach helps various stakeholders to become aware of, and articulate their needs, in a way that makes the design fit their needs, instead of adjusting their needs to fit the design (Buur and Larsen 2010). Owing to the service focus of our study, we chose to include tools and techniques known from service design, to support the participants' awareness of what constituted the service, and the context in question. The use of service design tools helped the participants to make sense of the intangible data-based service for maintaining the LEC database. Furthermore, altering the service design tools helped to represent data in ways that prompted workshop participants to consider data throughout the design process. Based on this, we suggest that in the context of service innovation, it is useful to supplement a participatory approach with service design tools, to create a pathway to foregrounding data in design.

7. Conclusion

This paper explores how data may be explicitly foregrounded in ways that enable domain experts outside the field of computer and data science to make sense of, and critically consider data and data schemata in collaborative design situations. A growing body of research is exploring ways to include data as input for design in collaborative design contexts. This study is different, in that we explored how data may become an object of design for domain experts, meaning that domain experts may consider and recognise data as something that may be designed. We show that it is possible to do so, by using carefully designed data notation, applying a close interaction analysis of three collaborative design workshops. We also present five lessons learned from our explorations. These include that (1) the tangibility of our proposed data notation supported the domain experts' discussions and critical reflection, which led to collaborative design workshops of which data was a more explicit part of the design. (2) Our explorations also showed that data is a difficult element to incorporate in co-design, because of the observed difficulty in distinguishing between data and the concrete situation it models. We suggest that this aspect should be considered when designing data notation. (3) Moreover, in our case, it was helpful to use multiple data representations throughout the design process. Our findings indicate that multiple forms of notation can complement each other when used together. (4) We find that supporting the domain experts' understanding of data as an object of design enables them to critically consider a data-based service's technical infrastructure (data and data schemata). (5) Finally, we find that participatory design is a useful approach for foregrounding data in a co-design context. Together, these lessons offer practical insights that may inform future work. We acknowledge that our study includes a number of limitations, and we conclude that more research is needed, to further develop the insights from this work.

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