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THE IMPACT OF DATA ON THE ROLE OF DESIGNERS AND THEIR PROCESS

Lu, Jiahao;
Gomez Ortega, Alejandra;
Gonçalves, Milene;
Bourgeois, Jacky

Delft University of Technology

ABSTRACT

With the advance of the Internet and the Internet of Things, an abundance of 'big' data becomes available. Data science can be incorporated in design, which brings forward various opportunities for designers to benefit from this new material. However, the designer's perspective and their role remains unclear. How do they think about and approach data? What do they want to achieve with this data? What do they need to take ownership of designing with data? In this paper we take a design perspective to map the opportunities and challenges of leveraging large data-sets as part of the design process. We rely on a survey with 75 participants across a Faculty of Industrial Design Engineering and in-depth reflective interviews with a subset of 9 participants. We discuss the impact of data on the roles designers can adopt as well as an approach to designing with data. This work aims to inform on educational support, data literacy and tools needed for designers to take advantage of this new era of design digitalisation.

Keywords: Big data, Design education, Design process, Designers' roles, Data literacy

Contact:

Lu, Jiahao
Delft University of Technology
Design, Organisation and Strategy (DOS)
Netherlands, The
lujiahao1994@gmail.com

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1 INTRODUCTION

With the advent of the Internet (network of knowledge) and the Internet of Things (network of senses), vast amounts of data are generated, from which scientists extract insights into human behaviours (Feinberg, 2017; Lazer et al., 2009; Thorpe et al., 2017). In this context, data is characterised by its large volume, its variety of multiple data sources and its velocity (in relation to data processing speed) (Laney et al., 2001). Examples of data could come from sensors, such as GPS location trace from GPS or equipment logs, but also social media data. As such, data tends to be extensive in numbers but usually lack context. This growing ubiquity of data along with a trend towards *datafication* (Lycett, 2013) can open up a promising avenue for designing with data. This approach enables to capture new insights about complex people's behaviour at scale to research, design and engineer human-centred systems, otherwise unavailable with more traditional methods (Bourgeois and Kortuem, 2019). While the use of this data remains in its infancy in the design process, the design research community shows an increasing interest in understanding how product, service and interaction designers can design with data as a creative 'design material' (e.g., Bogers et al. (2016); Bourgeois and Kortuem (2019); Speed and Oberlander (2016); Dove and Jones (2014)).

However, there are limited insights about how designers, outside these key publications, leverage data in their process. Firstly, the collaboration between data science and design can be problematic (King et al., 2017; Girardin and Lathia, 2017): while designers might struggle with a potentially reductive approach to rich contexts, data scientists, who specialise in processing data sets to extract insights, might find the design process too intuitive. Secondly, designing with data is an emerging trend and, as such, very little support is available for novice designers, who need guidance in finding which data should they use and for what purpose. It is still unclear the specific set of skills designers should have to design with data, a question related to data literacy (Wolff et al., 2017; Gray et al., 2018). Approaches to bridge data science and design are required to gauge the enormous potential of designing with data.

Thus, answering these issues are critical for developing appropriate design education, tools and mindsets to design with data. In this paper, we take a designers' perspective to explore what are the challenges and opportunities for designers when designing with data. For that purpose, we combined the insights from 1) a survey, which aggregates different design related profiles, with interest in using data, and varied degrees of data-design experience (75 participants); and 2) follow-up interviews with a sensitising booklet, with a subset of the survey respondents (9 participants). Our findings reveal the challenges and opportunities that lie ahead for designers when designing with data. Namely, we define the roles designers can and should adopt within data related projects and the activities that should be considered when designing with data. We conclude with insights and recommendations for design education and practice.

2 BACKGROUND

Thick data, such as qualitative data from interviews, sessions, and observations, has been applied in the design process for decades (Creswell and Creswell, 2017). The importance of thick data is recognised, and many research methodologies have been developed to trigger qualitative and contextual data (Bryman and Burgess, 1994). On the other hand, data generated in vast quantities from many connected products, services and systems, opens up opportunities for data collection and analysis at scale, providing precise and timely insights on human behaviour (Feinberg, 2017; Lazer et al., 2009; Thorpe et al., 2017). In design, this 'big' data is commonly used in the analysis of customer reviews (Suryadi and Kim, 2019) or product usage (Klein et al., 2019). Despite their distinct characteristics, 'big' and 'thick' data can offer a comprehensive understanding of users, their behaviours and context Pavliscak (2015). While big data can provide generalised insights that represent a large population, thick data can be used to understand the users' context, emotions and needs in an in-depth manner. Recent literature highlight that designing with data is often a hybrid approach, where thick and big data are applied subsequently and seamlessly (Seemann, 2012). Recent approaches that combine data throughout the design process include data-enabled design (Bogers et al., 2016), participatory data analysis (Bourgeois et al., 2014) and data stimulation (Dove and Jones, 2014), where data is used to prototype and generate knowledge from data-driven objects, (Cila et al., 2015) and through evaluation methods such as A/B testing (King et al., 2017). These approaches highlight the importance of blending thick and big data throughout the design process.

These hybrid ways of leveraging data in design led to a variety of distinctions. Data-driven, data-informed and data-aware (King et al., 2017), data-enabled (Bogers et al., 2016), and data-centric design (Bourgeois and Kortuem, 2019) are the most prominent nomenclatures for designing with data. Speed and Oberlander (2016) propose a framework that highlights three types of relationships between design, data, and the designer: 'design from', 'with', and 'by data'. This hints at different roles and relationship that operates between data and designers throughout the design process. Moreover, King et al. (2017) introduced a model on the designers' data mindset, which stresses a very dynamic and intentional weight of data in design decision throughout the design process. These two models capture the relationship between data and design from two perspectives, which are practice and mindset. While these key publications paved the way for defining an approach of designing with data, little is yet known about how designers actually experience projects involving data. In this paper, we explore how do designers think about and approach data in practice, to better understand *how can the design community prepare themselves better towards data literacy?*

3 PRELIMINARY FACULTY SURVEY

We conducted an initial survey study in the Industrial Design Engineering (IDE) Faculty, at TU Delft, the Netherlands. The aim of this survey was to map out designers' current data usage. Our team wanted to investigate their perceived confidence level when designing with data, as well as what challenges that may emerge. The IDE Faculty is a meeting point between novice designers, active practitioners and design researchers. Reaching out to MSc graduate students, PhD students, staff members – who are both active practitioners and academic researchers – provided us with a comprehensive spectrum of respondents interested in the topic of designing with data.

This exploratory survey had five sections: respondents' information including confidence with regards to data; data as a design material and associated challenges; usual design process; past projects involving data; and data-related tools. In this paper we will focus on the results regarding the participants' confidence level. The survey was answered by 75 members of the IDE Faculty, which includes Design Practitioners (10), Design Researchers (22), PhD Students (11), and MSc Graduate Students (23). Some members identified themselves as belonging to one or more of these categories and were considered as such for the analysis. We asked participants to provide information about their confidence in collecting and analysing quantitative and qualitative data as well as programming (using code for analysing data). An example of a question was '*how confident are you with collecting QUANTITATIVE data such as a location trace or a smartphone accelerometer?*'. We used a numerical scale from one to five, where one represented 'I have no experience' and five represented 'I am very confident'.

Our results show that participants generally feel more confident collecting and analysing qualitative data (respectively 76% and 83% answering 4 or 5) than quantitative data (respectively 32% and 31% answering 4 or 5). Design Practitioners, Design Researchers, and Graduate Students have the strongest confidence difference between data types. Design Practitioners, Design Researchers and PhD Students are among the population that feels more confident around quantitative data, even if their confidence level is not 'high'. When it comes to confidence around programming, there is no straight connection with data confidence. First, there is no clear trend for Design Practitioners and Design Researchers, whose reported confidence with programming was distributed across all levels. In contrast, half of the participating PhD students expressed high level of programming confidence. We observed the opposite trend for the Graduate Students. This might correspond to the fact that most of the PhD Students that replied to the survey already have some experience working with data and programming and not necessarily a background in design. The preliminary insights from this survey confirm our assumptions that using quantitative data as part of a design project brings a number of challenges, if only intimidating the designer. Like engineers in other disciplines, designers are trained to self-teach themselves in new skills and tools. However, training themselves in the meaningful use of data appear as a challenge. While introducing programming fundamentals in design curricula might equip designers better, this insight hints at a more significant impact of data on the designer's practice.

4 FOLLOW-UP INTERVIEW AND SENSITISING BOOKLET

To further investigate the roots of designers' lack of confidence around quantitative data, we designed an in-depth follow-up study. The goal was to qualitatively explore designers' reflections on their

experiences with data-related projects and explore the impact of data in their process. This follow-up study included a sensitising booklet and semi-structured interviews, for a combined in-depth approach.

4.1 Participants

After one initial pilot interview, we invited nine respondents from the survey to take part in the follow-up interview. We selected these participants based on their experience with data, actively looking for diverse perspectives among different fields and backgrounds. Table 1 summarises this information, highlighting the type of data the participants mostly used in past projects. Note that the large majority of participants mentioned numeric data, in high volumes, which cannot usually be dealt with manually.

Table 1. Details of interview participants.

Participant	1	2	3	4	5	6	7	8	9
Identification	Design Practitioner	Design Researcher	Design Researcher	PhD. Candidate	PhD. Candidate	PhD. Candidate	PhD. Candidate	Graduated Student	Graduated Student
Academic Background	Industrial Design	Communication Design	Computer Science; Interaction Design	Service Design; Data-Driven Design	Interaction Design	Integrated Product Design; Mechanical Design	Human-Computer Interaction; Interaction Design	Strategic Product Design	Strategic Product Design
Special Field	Digital Product Development; Information Design	Medical Device Design / Behavior Change	Involve Computer Technology Effectively In The Design Process	Sensor Data Application; Design For Healthcare	Urban Algorithmic System	Evidence-Based Design; Design For Healthcare	Service And Product Innovation	Service Design	Experience Design
Experienced data types	Sensor Data; Internet of Things Data	Online Survey; Anthropomorphic Measurements	Sensor Data; Internet of Things Data	Biometric/Health Data; Online Database	Gps Data; Sensor Data	Sensor Data; Online Text Data	Hospital Datasets; Prototype Data	Internet of Things Data; Operation System Data	Check-In Kiosks Data

4.2 Sensitising booklet

As a mechanism to help participants reflect on the impact of data on their design process, we prepared a sensitising booklet. The booklet was sent to each participant, prior to the interviews, which served multiple purposes: First, participants were able to prepare in advance and reflect on their previous experiences with data (Stappers et al., 2010), by applying the path of expression (Sanders and Stappers, 2013). As such, participants could think about the present situation, by relating to their previous experiences, which could reveal underlying needs and values. Second, the filled-in booklets were used as interview stimuli (Crilly et al., 2006) to encourage participants to express their experiences during the interview. Third, the booklets provided graphical data, which were used as further research material. We designed the sensitising booklet in three parts: data for designers, data in practice, and the relationship between data and design.

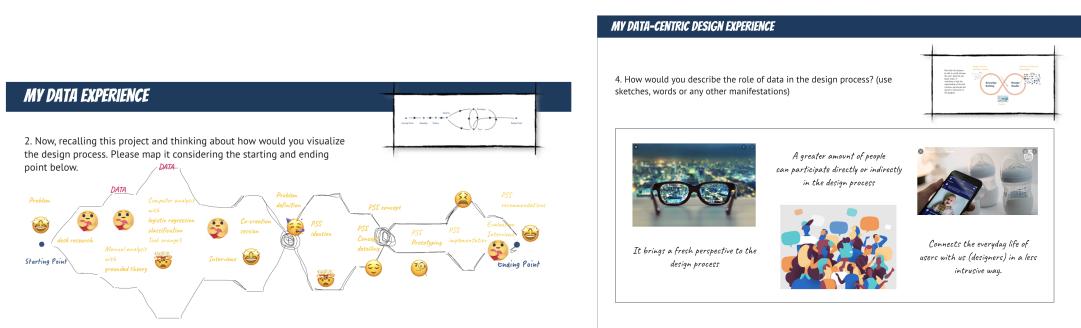


Figure 1. Examples of filled in sensitising booklet pages

- Part 1 focused on the current role of data for designers. Participants had to complete small assignments, such as defining design and data with their own words or visuals. This provided an easy and fun starting point for the booklet.
- Part 2 looked at the way designers deal with data in practice. Participants were asked to reflect on specific data-related projects, by visualising it and pinpointing their "emotion journey".

- Part 3 discussed the relationship between data and design, with questions like "*what do you like/dislike most about engaging data in the design process*". It gave participants the opportunity to look across all their experiences and reflect on the overall impact of data on their design process.

We sent the booklet to the participants digitally prior to the interview. We received all the filled booklets on time to prepare the interviews, including six fully completed. Three participants were unable to finish it all on time. In those cases, we covered the missing elements as part of the interview.

4.3 Semi-structured Interviews

Each sensitising booklet provided the leading cues for each participant's interview. This included following the 3-part structure of the booklet, as well as personalising questions based on the participants' reflections. The goal of the interviews was to reveal the context of the participants' experiences in projects involving data. To uncover insights that could clarify the survey's results, the following questions were included: 'Why did you choose these methods to deal with data?', 'Were there any difficult/inspiring moments when you used these methods?' or 'Which methods/tools have been the most valuable and helpful for you?'. To explore the participants' perception on the relationship between data and design, we asked questions such as 'How did the application of data in the design process changed over time for you?', or 'Could you name the two most important insights on applying data in the design projects based on your projects' experience?'. Furthermore, we asked the participants to compare between their previous projects involving data and those without, to learn about what kind of impact data brings to the design process.

The interviews, which took place online and lasted around 1 hour each, were conducted by the first author. The interviews were recorded, transcribed and analysed using an iterative coding approach, based on thematic data analysis (Chun Tie et al., 2019). Most of the analysis was carried out by the first author, supported by the remaining authors. An initial coding iteration helped to immerse ourselves into the interview material and identifying the most important details. An intermediate coding enabled us to cluster categories based on similarities and differences within the initial codes, which revealed relationships between the categories. With advanced coding, themes were built, which helped to understand the impact of data on design and designers.

4.4 Findings

Our findings are based on impressions from the survey and the interviews, which were mostly focused on participants' experiences with a variety of data (such as sensor and Internet of Things data, as shown on Table 1). Our findings are structured along two main points: The challenges and opportunities for designers in designing with (big) data; Applying (big) data in the design process.

4.4.1 Challenges and opportunities for designers

All participants agreed on how important data is to interpret user behaviours and inspire the design process. However, as indicated in Section 3, the survey's results suggested that designers are, in general, not confident in designing with data. The interviews provided further insights behind the reasons for such lack of confidence, which can be summarised in the following points:

- **Overwhelmingness:** Six participants explicitly expressed to feel overloaded when collecting and analysing data, as reported by P3: "*What I hate about data is that it's a hell of a lot of work to collect it. That is, that might be painful or difficult, costly.*".. Due to the large volume of data available, designers tend to feel overwhelmed by having to choose the 'right' data. This is further increased by having to learn new tools.
- **Lack of expertise:** Even though there is a concrete need to keep pace with the new trend of designing with data, some participants reported that they struggle with applying data, due to a lack of skills. When asked about their data experience, P8 reported: "*Some data is not useful or some is not cleaned (...) I don't know how to deal with raw data. So, they have to be aggregated or they have to be computed by data scientists.*".
- **Challenging collaboration with data scientists:** Designers recognise the importance of involving experts, such as data scientists, possibly due to their lack of expertise. P2 revealed: "*We had a*

statistician for one of the projects, and she made the calculations. I have no idea what she calculated. In the end, I got a graph which told us what's important or not. But I have no idea, I couldn't do what she has done". However, even though data scientists are valued, as they are able to translate raw data into organised and visualised information, the collaboration between them and designers is seen as a challenge. Designers perceive it as a time-consuming and effortful experience to adjust to. They seem to be wary of this collaboration, due to a mismatch between the two fields. This is illustrated in the quote: "[There] tends to be a lot of miscommunication between technical and design people. That's just (...) because we come from different backgrounds, we have different ways of talking about it but we also have very different ways of thinking about this" (P5). Thus, the value that can emerge from this collaboration is curbed by limitations.

- **Need for a common language:** A number of participants indicated the need for a balanced team, where a common language between design and data science should be established: "There are so many new concepts that we are not used to. So then you need to be constantly going to the data science dictionary. Oh, they said, verification. Let's see what verification means in this context" (P6).

Despite these struggles, most of the participants consider that designing with data will be a ubiquitous activity in the near future. P5 reported: *"I think with a new generation of designers coming up, in many cases, they will find themselves working in environments where that's just the way things are done [the collaboration between designers and data scientists] so you are part of that culture from day one and you don't go through a period where you are very sheltered or sitting in your comfortable little design team with other designers"*. By involving data in design and the expertise of data scientists and other fields, our participants reported a need to adopt to different roles. For instance, P7 highlighted the importance of the designer as the lead: *"You have to really fight for. To have to hold the project, because you as a designer can make nice decisions"*. Another relevant skill that designers can bring to a data design project is empathy, as indicated by P3: *"Designers are familiar with the psychology of people, are familiar with the ethnographic aspects of knowing, knowing a certain context"*. According to the participants' experiences, the roles designers can adopt seems to be changing, with the expansion of the boundaries of the design field (Figure 2 on the left).

4.4.2 Applying Data in the Design Process

While reviewing the participants' experiences in practice, we noticed that data plays an essential role in the design process, as explained by P6: *"You can use data for research in the first phase of the design process, and that can be used to understand the behaviour of people, or experience of the person. And, you can also see data as part of the solution"*.

A number of activities within the design process were highlighted, where the involvement of data needs to be carefully integrated. Before data collection and analysis, participants suggested that preparation is required. This includes researching existing data sets, understanding data sources, deciding what data to collect, making plans for collection and analysis, and understanding its context.

Data collection was considered by the participants to be one of the difficult activities in designing with data, since they lack the skills and tools, especially on the data selection. The amount of data collected is often large and overwhelming, and much of it ends up being useless. It is important to clean and select the valuable data before analysing, which requires designers to find the right criteria for selection. This is illustrated by P1: *"The problem is that I have a lot of sources. For instance, telephone (...) and difficult apps which gather the information. In this case, there was too much information and I had to figure out what's most useful"*.

Concerning data analysis, participants usually integrate different types and sources of data (big and thick), to fully understand the context. How different data points are connected and organised provide designers insights, translating data into meaningful information. P7 reports: *"You have a temperature data, the temperature in the home. Okay, so then it's just number, so what do we do? Is this biased? Why do we need to know the temperature in the home? But it becomes interesting when you show the temperature over a day. So we now know there is a meaning behind it. When we entered the home, that was when we change the temperature. So you make new connections, and by making new connections, you make unorganised data, meaningful."*

Data preparation, collection and analysis (Figure 2 on the right) were highlighted by the participants as essential activities that permeate the general design process. As such, when designing with data, these

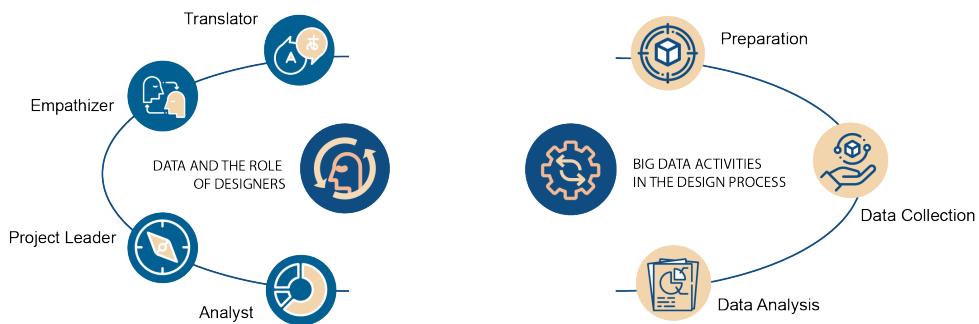


Figure 2. Overview of the main insights

three activities are iterated through at different moments of the design process, several times, from the early stages till the deliverable of the solution.

5 DISCUSSION

5.1 Data and the Role of Designers

In this section, we will discuss how involving data in the design process influences designers' roles and responsibilities. Our studies revealed that the roles designers need to play in the design process have multiplied, as more is demanded from them. This is consistent with prior literature (Speed and Oberlander, 2016; Yang et al., 2018), highlighting that, with the increasing use of data, and the development of machine learning, the products and services we design are becoming increasingly complex. As such, designers have moved from an expertise position towards adapting to other roles, which they have to switch to depending on the needs of the project context and the design phase at hand. Our results indicate that designers often play one or more of the following roles while designing with data: translators, empathisers, project leaders, and analysts.

- **Translator:** Designers seem to be often required to translate between fields. Through this role, designers can better take advantage of their collaboration with data scientists. However, for this role to be effective, designers need to be knowledgeable and equipped with technical jargon, besides having communication and empathy skills. This essential 'partnership' with data scientist is highlighted by Girardin and Lathia (2017) and Gorkovenko et al. (2020).
- **Empathiser:** This role encompasses one of the most crucial skills for designers and it continues to be vital in the big data era. Although sensors can capture detailed user experiences, it is necessary to adopt an empathising role to retrieve meaningful insights, as illustrated by Bogers et al. (2016).
- **Project leader:** While designing with data, the amount of information available increases exponentially, as well as its complexity. The project leader needs to guide a projects' direction and make design decisions for the whole team. According to our participants' experiences, designers tend to struggle with this role, as they are not usually the most powerful people in the project. However, designers' holistic approaches, combining factual and intuitive factors, can be beneficial for this role while designing with data.
- **Analyst:** Designers have always been required to analyse thick data, as a way to understand users' experiences and feelings. It is considered an essential step before empathising. Currently, these responsibilities also include being able to analyse other types of data (e.g., quantitative data, sensor data, location logs). As highlighted in the background section, the combination of both big and thick data can potentially bring the most comprehensive insights (Seemann, 2012; Bourgeois and Kortuem, 2019).

Designers should acquire and develop certain skills to be able to embrace these roles (Wolff et al., 2017). In particular, for the role of Translator, designers should become aware of the technical jargon to communicate effectively with data scientists and engineers. For the roles of Empathiser and Translator, designers should be able to make sense of data and tell (visual) stories about data for others to digest and engage. For the role of Project Leader, designers should be able to ask and answer questions through data. Finally, for the role of Analyst, designers should be able to decide what data to collect and how to process it.

Nevertheless, such roles can only be effectively applied when designers' confidence with data increases. This is particularly important for novice designers, whose tendency to feel overwhelmed by huge quantities of data seems to be an initial hurdle to surpass. In the next section, we elaborate on the particular activities where these roles might emerge.

5.2 Data Activities in the Design Process

Our research revealed three activities, which should be considered when applying data in the design process: Preparation; Collection; and Analysis. The three activities are not necessarily linear, but rather iterative, supporting each other.

- **Preparation activity:** Designers familiarise themselves with existing data sets and plan the data collection and analysis activities. This includes deciding which data should be collected and what methods should be applied. From the interviews, it was considered paramount to understand the value and potential of data during the preparation, including possible outcomes and problems data can provide answers to. This aligns with the Data-Aware mindset which is proposed by King et al. (2017). Our findings highlight that the use of thick data can help during the preparation activity to direct the focus of (big) data collection and analysis. The main goals of this activity are to reduce time and effort at later stages and to understand the potential value of data.
- **Data collection activity:** This is an iterative process where both thick and big data are collected from various sources and methods. Data scientists tend to be involved in this activity to help designers set sensors and other data collecting tools to capture the context.
- **Data analysis activity:** In this activity, data is analysed, using the appropriate tools for each type. This is difficult for designers, as they might feel overwhelmed by the amount of data collected. Feelings of anxiousness and fear of missing out important insights tend to emerge, and this activity tends to take much longer than expected. Designers, especially novices, usually lack data-related skills to do the analysis, which requires the support and involvement of data scientists. Issues that arise during this activity include miscommunication between designers and data scientists, where holistic and designerly approaches tend to clash with the rigorousness of data science (King et al., 2017; Kollenburg and Bogers, 2019). Furthermore, the designers' expectations from big data tend to not be completely met, specifically when only superficial insights are retrieved.

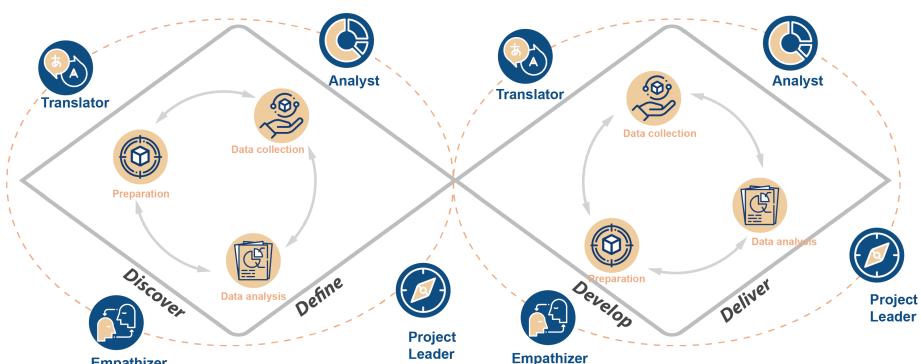


Figure 3. Role and process through the double diamond

Figure 3 connects these findings to the Double-Diamond model (Design Council, 2006), which highlights how the identified roles (Section 5.1) and activities (mentioned above) fit within the context of a typical design process. According to the current design with data approaches and our participants' experiences, the three data activities occur mainly during the Discover and Deliver phases. In the Discover phase, designers use data to understand users' experiences and needs. In the Deliver phase, data could be collected from prototypes, e.g., to evaluate concepts. Meanwhile, designers are invited to embrace the dynamic nature of data related roles throughout the design process, by shuffling between them at different moments, according to the requirements of different projects. It became obvious from our research that designers are not being sufficiently supported to rise to the new challenge of designing with data, especially during preparation, collection and analysis of data.

6 CONCLUSION

While a growing body of literature demonstrates the design benefits of big and thick data as stand alone and in combination (Dove et al., 2017; Bogers et al., 2016), this comes with new practical challenges for designers. In this paper we report on an investigation of these challenges through a survey and in-depth interviews. Nevertheless, our insights should be considered in light of a number of caveats. The research was conducted in an academic environment, so it might be possible that different insights could be captured among wider groups. Furthermore, the data types involved in this research could not cover the myriad of big data sources available. We highlighted the impact of data (e.g., sensor data, GPS logs, or social media data, to just name a few) on the role of designers and their process, stressing a challenge beyond programming and data analysis skills. A change of the designer's role is not confined to designing with big and thick data. This is also pointed out in the context of participatory approaches (Ribeiro et al., 2020, Chapter 2). Along with a growing effort to incorporate digital knowledge and skills in design education (Beghelli et al., 2019; Zakaria and Lim, 2018), our insights suggest that data literacy for designers goes beyond technical challenges. It requires dedicated preparation to these new designer roles and a wide skill set ranging from obtaining meaningful insights from data to communicating insights effectively, in a way that can be digested by others. In this way, we will be able to take full advantage of designing with big and thick data.

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