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Master of Arts thesis abstract

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Title of thesis Data as a design material: An analysis on the challenges of working with “big data” related technologies in an industrial context

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Abstract

In recent years, the ability to collect, store and analyse large datasets by private companies and government agencies has increased to the point where the term “big data” has been coined to describe the phenomena. Alongside “big data”, several data processing technologies are becoming more widespread due to their effectiveness and success in everyday products and services; these are artificial intelligence, with its subsets machine learning and deep learning, and data analytics amongst others.

This study investigated the challenges designers face when working with new information and communication technologies in an industrial context. More specifically, it deals with “big data” and new data processing technologies and how designers engage with them as a design material when envisioning new products and services. The research questions were (1) what challenges are designers facing when working with “big data” in a data-rich industrial context? (2) how is working with “big data” and new data collecting and processing technologies different from other design materials? (3) how can designers overcome some of the challenges of working with data? This thesis adopted a research through design approach and data was collected between June 2015 and January 2016. Furthermore, a review of the material-centered design literature was used as a theoretical framework.

To answer the research questions, this thesis investigated a six-month design project done for the energy company Vattenfall. Vattenfall was at the time going through a digitalisation phase and was interested in evaluating the possibility of combining their internal data with other data sources to explore new products and services. During the six-month period, I worked in Vattenfall’s Helsinki offices, designing different concepts under the supervision of the product development team and their programme manager as my direct supervisor. Data was gathered using different qualitative methods and focusing in three areas: the design practice, the design outcomes, and the interactions with the team and stakeholders.

The key findings demonstrate how the practice of design in this new technological landscape faces multiple challenges. The main challenges being (a) the high level of complexity of these technologies, (b) the lack of education/experience of the designer to work in this context, (c) the lack of competence in the organization and (d) the missing frameworks and tools for collaboration between data experts and designers. Furthermore, it was also found and validated against the literature that these new technologies present different properties not comparable with previously well-studied ones like haptics, Bluetooth and RFID. Making existing frameworks and traditional approaches to exploring new digital materials hard to replicate. The results further suggest the need for developing novel concepts and frameworks to support new ways of understanding, describing and working with “big data” and its related technologies.

Keywords design material, design for the private sector, research through design, big data, data analytics, utilities sector

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Data as a *design material*:
An analysis on the challenges of working with “big data” related technologies in an industrial context

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Digital material: Technology when seen in a design context
HCI: Human computer interaction
ICTs: Information and communication technologies
UX: User experience
AI: Artificial intelligence
ML: Machine learning
IoT: Internet of things
RtD: Research through design

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1. Introduction

1.1 Background

This thesis emerged from a practical thesis work I did for the energy company Vattenfall. During the year 2014, together with four other design colleagues, I participated in a project through Aalto University to re-design one of Vattenfall's products. A few months later after finalising that project early in 2015, I contacted our Vattenfall supervisor in the previous project with the intention of collaborating further in the future. The supervisor, a senior product manager working in the Finnish offices of Vattenfall, proposed me to work for six months during 2015 as a thesis worker. After discussing back and forth the topic of the thesis, we agreed on the design brief that I was to develop in six months during 2015, starting in June 1st and presenting the results in December. The initial brief read: "to analyse the current state of Vattenfall's user data and combine it with external data through a design process, to generate new possibilities regarding services and business models". In this context, I joined the product development team in the Finnish offices, where I worked alone on the brief as an interaction and concept designer, with the assistance of the product team. As a result of this practice, three different design concepts were developed and presented in Vattenfall's Finnish and Swedish offices at the end of the process.

The thesis was compiled after the design concepts were presented to Vattenfall and therefore it deals with different questions and challenges that emerged during and after reflecting on the practice; namely how designers engage with data as a digital material.

1.2 Problem formulation

This thesis is concerned with exploring the new challenges that designers face when working with new information and communication technologies (ICTs). More specifically, it deals with "big data" and its related technologies and how designers as non-IT professionals try to cope with the complexities that these new technologies represent. The main problems being a) trying to understand the abstract properties and functionalities of these technologies in order to incorporate them into products and services, b) the impossibility of exploring all available technologies and c) the difficulties of prototyping with specific technologies (Yang, 2018).
In recent years, there has been a growing interest by HCI and design researchers in

exploring the properties of different technologies through a design and material lens (Wiberg, 2014; Zimmerman, Stolterman, and Forlizz, 2010). In other words, establishing a reflective conversation with the material through direct interaction with it (Schön, 1984). This way of engaging with technology as a design material aims at exploring the properties of new technologies, revealing what is possible and generating a space for innovation. However, research has focused mostly on specific technologies (Wiberg, 2014). This means that one single technology such as Bluetooth is explored and by direct contact with the material through rough sketches or early prototypes, this allows the practitioner to "feel" and understand the technology better (Sundström et al., 2011). However, design practitioners are not always provided with a particular technology in beforehand; instead, they are given a broader technological scope to choose from, something that creates a different type of challenge: How to explore possible technologies as design materials when they are not specified in the design brief.

In his seminal analysis of the design practice and its engagement with new materials, Manzini stated: "

> *"The boundary now separates those who work with the question, "What is this?" (for whom specialised and vertical knowledge is still useful) and those who work on the question "What do I need, and why do I need it?" (for whom new bases in the relationship with the possible must be established)".*
> *(Manzini, 1989, p. 55)*

As designers from different areas face more and more the challenges presented by new information and communication technologies, the rate of technological development keeps increasing. The question "what is this?" representing specialised knowledge and aimed at understanding one particular material better, would prove insufficient due to the current speed at which new digital technologies are being developed and their complexity. Moreover, new technologies such as machine learning, require a large amount of data and resources to even generate a working prototype, making traditional design approaches ineffective (Yang, 2018). Quick prototyping through an iterative process is simply not a feasible approach when working with some of these new technologies.

Analysing technologies one by one would be an insurmountable endeavour, let alone creating a system of classification for each technology (or updating existing ones). Questions that would remain unanswered after designers get to understand one particular technology better, would be: Will they be able to share that knowledge, and how? Will they need to go through the same process if they have to deal with a different technology or if that technology changes? Will they have the time and resources to explore multiple technologies if the technological choice is broad?

This thesis will explore these problems and questions and reflect on possible paths to move into the direction of a "what do I need, and why do I need it?" design mentality.

1.3 Objective, research questions and scope

The objective of this thesis is to explore the challenges of working with "big data" sources and new data processing technologies as a *design material* to create novel digital solutions. In doing so, it will additionally open up a discussion on whether the inclusion of the aforementioned digital materials is an issue that concerns only the interaction design field or the broader design community. In order to do so, this thesis will analyse a design project developed in the utilities sector. The project is a user interface project I developed for an energy company (Vattenfall). Different prototypes were designed in six months during 2015, in which multiple "big data" sources were incorporated in the design process to produce the final concepts.

Vattenfall's design project started in June 2015, with two final presentations of the concepts done in December 2015 and January 2016. It provides insights into the designer's perspective when working with new ICTs in the context of a large organisation within the utilities sector and in a data-rich industrial environment. It analyses the design process by following the ideation, sketching and presentation of different design concepts that incorporate multiple data sources. It does so by focusing particularly on the difficulties of understanding new data collecting, storing and processing technologies and abstracting them in order to incorporate them into the design process. Furthermore, by studying the communication between the designer, stakeholders and team members, this study highlights the importance of the organisation and its digital maturity as necessary enablers of design innovation.

Data was collected throughout the design practice using different methods, all of them which can be categorised as qualitative. Following a research through design methodology, this thesis focuses mainly on three areas to collect and analyse the data: a) the design process, b) the design outcomes and c) the interaction with the team and stakeholders. The primary data source to capture the design process is the design process notes; a physical and digital diary where I wrote down and sketched the different steps of my process. As for the design outcomes, the data collected during the practice was divided into two. First, a collection of sketches and prototypes were collected in both paper and digital format, and additionally, design notes were also collected. These are digital and paper entries in a diary, where rough sketches have notations describing the rationale behind the decision making. Finally, to investigate the interaction between the designer and the organisation, eight interviews with internal stakeholders and team members were held during and after the design practice. Each interview lasted for approximately one hour. Additionally, e-mail records containing internal communication were also collected, and participatory observation notes taken mostly during meetings and internal presentations.

The data analysis was done in two stages. One after the completion of the design concepts and presentations to Vattenfall, when I gathered all the material that I had used and created for the company to form the final report. The final report was a collection of design research, processes and frameworks used, sketches, final prototypes, feedback and implementation discussions that I provided to Vattenfall. This was done in February and March 2016. In January 2018, I analysed the data in the broader context of the research through design practice, including interviews, e-mail communication, participatory observation, etc.; to build and contextualise it. Together, the two stages of data analysis provide a full and clear picture of how the design process progressed and evolved during those six months. The contextual data adds details on how the interactions with different members of the organisation influenced and impacted the design process.

Research questions
Research question 1:
What challenges are designers facing when working with "big data" in a data-rich industrial context?

Research question 2:
How is working with "big data" and new data collecting and processing technologies different from other design materials?

Research question 3:
How can designers overcome some of the challenges of working with data?

The research questions will try to be answered by first analysing the literature on the topic in section 2, with the aim of providing context to the problem and creating a framework to later presenting the practice. Second, in section 4, a research through design practice will be presented where the designer is faced with the challenges earlier discussed in the literature. And finally, by reflecting on both the theory and practice together in sections 5 and 6.

2. Research background

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The goal of reviewing the following literature is to understand how design research and practice is coping with a new set of technologies that present characteristics unknown to most designers. In order to do so, it is essential to understand what are these technologies, why are they different and what are their distinctive characteristics.

Furthermore, another crucial aspect of reviewing existing literature on the topic is to analyse whether designers are facing the same problems when trying to work with these technologies. The design field is continuously changing and growing; however, new technological developments affect every industry, therefore reflecting on current practices across the design spectrum is indeed relevant. By understanding the problematic other designers are facing within this technical domain, a reflection on my practice will gain depth, perspective and context.

2.1.1 Design, data and "big data"

For decades, designers have given data different uses. First, in data visualisation related tasks, with the Information Design Journal first publication in 1979 and Edward Tufte's The Visual Display of Quantitative Information in 1983 opening a whole new field for visual designers. In the last decades, the Internet and digital technologies have made it possible for interaction designers to improve the user experience of digital products and services by quickly testing different hypotheses with millions of customers, using the term data-driven design to define this process (King, 2014; Giaccardi et al., 2016).

Interaction design was the first field to deal with the fast development pace of new information and communication technologies. First by designing interfaces for users to interact with the systems, which became the field of Human Computer Interaction (HCI) within computer science in the early 1980's. Later on, moving into social computing, mobile interaction, information architecture, etc., now under the bigger umbrella of user experience design (Carroll, n.d.). However, as information and communication technologies became ubiquitous, designers beyond HCI started to face the challenges presented by the new digital landscape. Graphic designers work in web and mobile design; service designers have to consider both the off-line and on-line journey of the user and industrial designers are incorporating sensors in their products. As of today, it's safe to say that the majority of designers ranging from textile to furniture, deal with information and communication technologies (ICTs) in one way or another (Belenguer, 2015, p. 8).

In recent years, the ability to collect, store and analyse large datasets by private companies and government agencies has increased to the point where the term "big data" has been coined to describe the phenomena (Ward, 2013). Debates about ownership, privacy, technology and value are currently ongoing, involving a plethora of varied interest groups. Furthermore, in 2011, Gartner, Inc., the world's leading information technology research company, stated that "Information is the oil of the 21st century" (Gartner, 2011). Previous questions about whether big data would help us create better services and tools (Boyd & Crawford, 2014) have been answered positively in the last few years. There are now plenty of examples where both the private and the public sector have benefited from using these large data sets (Kitchin, 2014; McKinsey, 2011). From spam detection filters to predictions about estimated driving time, speech to text translation, image recognition, or improving health diagnostics, large data sets coupled with new technologies to collect, structure and analyse the data are being implemented across several industries (Dove et al., 2017; Holmquist, 2017).

2.1.2 The technology behind "big data": artificial intelligence and machine learning

Since the early days, the advancements in computer science created the expectation that one day, computers would be able to surpass humans in most tasks that required brainpower. While it is clear that some tasks such as playing chess were mastered by computers, as demonstrated by a chess engine running on mobile phone defeating a grandmaster (Hiarcs Palm Chess Rating, 2005); other general tasks such as recognising objects or animals in photos turned out to be more difficult than expected. Artificial intelligence remained an unfulfilled promise.

Nonetheless, after 2010, breakthroughs in artificial intelligence together with fast developments in other industries like data science, data processing hardware and graphics processing units, created momentum again (Holmquist, 2017). A great example and a breakthrough moment for artificial intelligence was the 2012 image recognition competition called ImageNet Challenge. ImageNet is a large visual database, designed by a group of researchers from Stanford and Princeton universities. The database contains millions of images, all labelled by humans: for each word such as "dog" or "apple", the database contains hundreds of images. The goal of the ImageNet Challenge is to "estimate the content of photographs for the purpose of retrieval and automatic annotation using a subset of the large hand-labelled ImageNet dataset (10,000,000 labelled images depicting 10,000+ object categories) as training" (ILSVRC2010, 2010). In 2010, the winning system could correctly identify and label an image 72% of the time (ILSVRC2010, 2010). In 2012, a team from the University of Toronto, using a technique called "deep learning", made a breakthrough and achieved an 85% in accuracy (ILSVRC2012, 2012).

Artificial intelligence
AI is the broadest term, applying to any technique that enables computers to mimic human intelligence, using logic, if-then rules, decision trees, and machine learning (including deep learning).

Machine learning
The subset of AI that includes abstruse statistical techniques that enable machines to improve at tasks with experience. The category includes deep learning.

Deep learning
The subset of machine learning composed of algorithms that permit software to train itself to perform tasks, like speech and image recognition, by exposing multilayered neural networks to vast amounts of data.

Figure 1. A glossary of artificial-intelligence terms (Parloff, 2016).

The following years, other teams researched and implemented deep neural networks to their models, reaching an accuracy of 96% in 2015.

Some of the techniques used in the ImageNet Challenge were not new. Particularly, the technique called "deep learning", which used neural networks, was a concept that had been around since 1950's (Louridas & Ebert, 2016; A brief history of neural nets and deep learning, 2015). Deep learning, a subset of machine learning, emulates the way a human acquires a certain type of knowledge: a system that uses deep learning can be trained by feeding it data, for example, labelled images of a "cat". In the first few iterations, the data can be structured for the model to reach a certain level of accuracy. Deep learning programs then build, after several iterations, a predictive model of what "cat" looks like. The program will look for pixel patterns that define what a "cat" is; having four legs, for example. After each iteration, the model becomes more complex, adding more "features" to the output and feeding it to the next network as input. This not only yields more accurate results but has also proven to be faster than other machine learning techniques (A brief history of neural nets and deep learning, 2015).

Nonetheless, why, only after 2010, deep learning became so popular? (Yang, 2018). A few things were standing in the way of the deep learning breakthroughs. First, it would take a long time to train the program, sometimes weeks and it would also take a long time to get a reply from the system, something critical in new real-time applications like speech recognition. Second, the training data was just not available. Labelled databases were exponentially smaller than what they are today. And thirdly, the algorithms and techniques had to be tweaked (Holmquist, 2017; A brief history of neural nets and deep learning, 2015). Since 2010, the exponential increase in computational power, coupled with the "big data" phenomenon that had companies like Google, Facebook and Amazon gathering billions of data points over the years, meant that those barriers holding back deep learning and machine learning were no longer there (Holmquist, 2017).

These new advancements within machine learning and artificial intelligence quickly attracted capital for both research and development. In 2011, Microsoft introduced neural nets into its speech recognition features; in 2013 Google used neural nets to improve the photo search; in 2014 Google acquired DeepMind, a startup specialised in deep learning and reinforcement learning, for 600 million dollars; in 2016 DeepMind's AlphaGo defeats the Go world champion using deep learning techniques. The technology proved to be not only successful but also flexible. Commercial applications have reached the healthcare sector, supply chain and financial institutions, to name a few. The technology can now be found in some of the most used products around the world: Netflix, Spotify and Gmail.

With machine learning and deep learning guiding the way, artificial intelligence is projected to reach a global business value of 1.2 trillion (USD) in 2018, an increase of 70% from 2017, according to Gartner (2018). Louridas and Ebert (2016) state that machine learning is "the major success factor in the ongoing digital transformation across industries". Reflecting on his years of experience at Google developing machine learning user experiences, Lovejoy suggests that just as mobile created a revolution for designers and the web before it, "machine learning will cause us to rethink, restructure and reconsider what's possible in virtually every experience we build" (Lovejoy, 2018).

2.1.3 Designing in a new technological environment

To add to the big data and artificial intelligence phenomena, now the "internet of things" (IoT) through connected objects that collect data from the world, has opened up new possibilities for designers (Kuniavsky, 2010; Rose, 2014; Rowland, 2015). This means designers have at their disposal data coming from mobile phones, weather sensors, electricity meters, toothbrushes or cars that are being collected every second. However, as mentioned above (2.1.2), the real value of the staggering amount of data that is being collected is in the way it is being processed.

Both big data and IoT phenomenon have created new challenges and opportunities for designers, who are trying to use these massive data sets not just to evaluate design decisions or to visualise it ("designing *from* data"), but as another *design material* to create new products and services ("designing *with* data") (Giaccardi et al., 2016; Kuniavsky, 2010). As the number of connected devices and collected data exponentially grow, so will the challenges and complexities for designers.

The design and development of new products and services that integrate ICTs in one way or another is a highly complex task that involves professionals from different fields such as computer science, electrical engineering, product and service design, software engineering and data science, to name a few. Communication and collaboration between these multidisciplinary teams are essential so:
a) each member's expertise is used to the fullest
b) use the full potential of new technologies; being hardware or software
c) "Avoid fighting with the technology to make it fit the goals of the interaction; and instead use the potential of the technology to shape the interaction in dialogue with the multidisciplinary design team and user-centered methods" (Belenguer, 2015, p. 5)

It is in this context that designers need to explore ways to not only understand new digital materials but to communicate user needs and design questions back to the team and organisation.

Engineers have traditionally focused on technology, either by developing new technological capabilities or by solving problems through them (Louridas, 1999; Belenguer, 2015). On the other hand, designers have been involved in creating applications and combinations of existing technologies. They innovate by re-purposing and giving new meaning to technology, considering what could be valuable for people (Norman, Verganti, 2014). Norman and Verganti bring up the example of the Nintendo Wii, that used technologies that were rejected by other video game console companies at the time and focused on meaning change: "video games for all". The technologies used were accelerometers and infrared sensors, both costing very little money (Norman, Verganti, 2014).

New ICTs like big data or machine learning, due to their complex nature and intangibility, are proving harder to innovate with. Even if the technologies have been advancing rapidly, as in the case of machine learning, design innovation has not followed (Yang, 2018). "*Today, it seems that ML* (machine learning) *systems are as creative and interesting as the data scientists that make them*" (Dove et al. 2017). Designers in the aforementioned new multidisciplinary teams have the opportunity to contribute to re-purpose and redefine these technologies, by conceiving what they might do and for whom.

This has led to a growing interest in researching new technologies through a material lens, with the aim of allowing practitioners with no engineering background to utilise new technologies as a design resource (Yang, 2018; Belenguer, 2015; Wiberg, 2014).

2.2.1 Early changes in material development

In 1989 Manzini reflected on the challenges and opportunities that designers faced at the time due to new material developments. These new material advancements, he argued, created a crisis in the traditional way we engaged with materials, preventing designers from giving them meaning and perceiving their properties and potentiality (Manzini, 1989, p. 31). Traditionally, identity was conferred to materials through a long process of testing and cultural history, allowing practitioners to address materials by names, consolidating a language to refer and work with them. The name given to materials became an abbreviation for the "set of relations between conditions of use and performance that typified that material" (Manzini, 1989, p. 32). This process, however, was based on two conditions:

"- There were few materials and they were quite distinct one from another, so that each corresponded to a well-defined field of relations;
- Materials remained constant over time in terms of qualities and properties, and their variations (or the introduction of new materials) were slow enough to allow the adaptations of the system of meanings" (Manzini 1989, p. 32).

The new wave of materials development such as smart and computational materials had moved the design practice into an unknown territory for which it needed to adapt (Manzini, 1989, p. 32). When working with these new materials, he suggested designers should stop asking "what is it?" and start asking "what does it do?"

Manzini's work had a profound influence in design research and practice (Bergström et al., 2010). It brought to light early on to a problem that had just started, and was projected to grow in the following years. With the latest evolution in ICTs, this became a widespread phenomenon and challenge across the design practice. Traditionally, industrial designers had to deal with new materials such as plastic, graphic designers with new coatings and printing systems, etc. Each design field dealt in isolation with new material developments. However, due to how ubiquitous ICTs are, the material problem of new digital technologies has moved from being an interaction and HCI only to: textile, service, graphic, and even furniture design (Belenguer, 2015, p. 8).

2.2.2 Technology through a material lens

In recent years, designers from different backgrounds became more and more involved in projects that deal with technologies such as big data, machine learning and networked objects (IoT). HCI and interaction design were the first fields to deal with the complexities of new ICTs and user interactions with computing systems (Carroll, n.d.). Designers needed new methods to engage with digital developments so they could discover and explore the material properties of these technologies. Following Manzini's work, the goal of design was to understand what was possible and what was thinkable in the new digital context.

As mentioned before, the traditional material view is that designers explore materials in a studio or a workshop, where they are used to shape, build and play with different elements; typically paper, wood, clay, etc, to develop tacit knowledge of what is possible (Buxton, 2007). The underlying assumption is that the direct contact with materials enables a deeper understanding and stronger relationships between actors (designers) and materials. Designers engage in what was articulated as a "conversation with the material"; as stated by Schön: ''the material talks back to the designer'' (Schön, 1983; Wiberg, 2014). However, when designing with new digital materials (data, software and hardware) designers struggle to interact with them because of their immateriality and intangibility (Ozenc et. al., 2010). Therefore, new digital materials require the creation of concepts, to support "ways of understanding, describing and working" with them (Bergström et al., 2010).

Ozenc et al. analysis on the shortcomings of designing with software demonstrate the challenges designers face when dealing with immaterial components (Ozenc et al., 2010). Their analysis focuses specifically on software but can be extrapolated to most ICTs. First, the authors mention how the material nature of new digital materials keeps constantly changing, due to hardware updates and new programming languages introduced. This presents the first challenge for designers. They further name three pitfalls designers experience when trying to have a 'conversation' with the material of software:

a) Tools that support interactive prototyping systems do not encourage an iterative process to refine interactive behaviours

b) Designers with no development skills lack the competence with development tools to sketch with software directly

c) Designers find it challenging to communicate the vision that they seek to developers. The authors suggest this is caused by designers not knowing what they want, as they do not have the opportunity to reflect, especially on a detail level (Ozenc et al., 2010; Purgathofer & Baumann, 2010; Myers et al., 2008; Newman & Landay, 2000).

In order to generate a reflective space with the materials of software and hardware, different fields and particularly HCI have seen a growing interest in the “closeness to materials”. Borrowing methods from design and crafts, they are engaging directly with the materials in the context of digital development (Wiberg, 2014). Different methods have been applied to analyse new digital technologies as creative materials in the ideation design process to create meaningful user experiences (Bücker, 2017; Wiberg, 2014). An example of this is ‘inspirational bits’, a research project with the objective of exploring ways for practitioners to become familiar with digital design materials early in the design process. The idea of inspirational bits is to create ‘quick and dirty’, rough yet fully working sketches that make visible the different properties of a given material, such as Bluetooth and RFID. They do so by transforming the technology into an experience (Sundström et al., 2011). This allows the practitioners to understand the digital material better and to generate a space where different and novel ideas can emerge (Sundström et al., 2011).

In his doctoral dissertation, Belenguer states the following when discussing the material turn in human-computer interaction:

> *“If technology is approached with a material perspective, it could be worked and crafted as material with properties, and they could be combined with different materials in the same way as wood, glass, or leather, making them suitable for a design process that explores and exploits the material to its fullest to deliver the user experience. Technology can move from the “material without qualities” to a material that shows its properties and qualities, making them suitable for design”.*
> *(Belenguer, 2015, p. 20)*

2.3 New technologies, new challenges

The material and design approach to technology has been researched and implemented in different areas. From Bluetooth, haptics, wireless sensors networks and movement sensors, different technologies have been the focus of research, especially in interaction design (Wiberg, 2014; Belenguer, 2015). Those technologies tend to involve both the digital and the material world, as they are either incorporated or communicate with material objects and products. However, a new set of technologies that are becoming ever more present do not exhibit the same properties as the older generation. These are machine learning, artificial intelligence, data science and deep learning.

What makes these technologies different from motion sensors, Bluetooth or RFID? Firstly, these new technologies are much harder to categorise. Researchers would previously take a technology like Bluetooth, break down its defining properties and then explore the possible activities related to the capabilities, the domains connected to the activities, and then the users connected to the revealed domain (Wiberg, 2014; Yang, Banovic, Zimmerman, 2018). On the other hand, the new technologies’ capabilities are “wedded to its dataset, labels and underlying algorithm” (Yang, 2018). Its value and possible applications are revealed after multiple interactions over a longer time period. Furthermore, as mentioned in 2.1.2, artificial intelligence saw a breakthrough around 2012 when computational power, massive datasets (“big data”) and smarter algorithms proved finally to be effective at solving particular tasks that seemed impossible just ten years before. The differences, therefore, are considerable: a) In contrast with previous technologies like motion sensors, haptics, Bluetooth or WiFi, the resources needed to work with e.g. deep learning are exponentially more substantial (Yang, 2018); especially considering the kind of computational power needed. And b), while previously researched technologies used relatively cheap hardware and a power outlet or batteries, the new technologies now also require massive datasets.

Just recently, research on the material and design approach to these new technologies has been advanced, focusing on technologies such as machine learning (Yang, 2018, Yang et al., 2018a) and artificial intelligence (Rozendaal et al., 2018; Holmquist, 2017, Lovejoy, 2018). The aim of this research, as it had been previously done with other technologies, is to understand how designers and non-IT professionals can engage with them to discover different and novel applications (Yang et al., 2018). It is no surprise that designers are facing new and difficult challenges giving the nature of these new digital materials.

Before discussing each challenge one by one, it is worth noting that some of this research is explicitly aimed at HCI and UX designers (Deve et al., 2017; Carmona, Finley & Li, 2018; Yang, 2018; Yang, Banovic & Zimmerman, 2018; Yang et al., 2018b). Although the new technologies being studied concern designers in general, it is understandable that the first wave of research is coming from design fields closer to computer science. This is another problem that will be studied later; namely, that UX/HCI designers are by the nature of their work already much better prepared to deal with the complexities of new ICTs. Other design fields that are further away from computer science, but that will be forced to deal with its complexities sooner or later, will have an even harder time to grapple with the new technological challenges. Nonetheless, it is worth exploring the current hardships UX and HCI practitioners are facing when working with data related technologies.

a) Understanding AI / ML
The first challenge is the designers' lack of understanding of what artificial intelligence and machine learning can and cannot do (Holmquist, 2017; Carmona, Finley, & Li, 2018). Dove et al. (2017) a surveyed fifty-one UX designers, asking them about their challenges when working with machine learning. They found that the majority of the respondents had difficulties understanding what machine learning was and what it could do. Because of this, designers have a hard time to "envision uses that don't yet exist" (Dove et al., 2017). In their literature review covering twenty years on the topic (Dove et al., 2017), the authors found generalisations about the topic but very little on the specifics "about what is needed to design with it".

b) Prototyping
Second, the difficulties of prototyping: "ML clearly demands a new type of prototyping, one that does not yet exist". (Dove et al., 2017). One of the respondents in Dove et al.'s survey stated, "...making interactive prototypes that incorporates machine learning is hard (haven't found a way to do that yet in an easy fashion)" (Dove et al., 2017). Lovejoy (2018), reflecting on his experience at Google developing products that integrate artificial intelligence, says the following regarding prototyping machine learning models: "takes an incredibly long time to build and instrument (and is far less agile or adaptive

than traditional software development, so it's more costly to swing and miss)". Moreover, the amount of data required to generate a working prototype with these technologies is extremely large, and only a handful of companies are able to access it (Yang, 2018). Adding to this, designers do also have a hard time prototyping for data that "is dynamic at a large scale" (Dove et al., 2017).

c) Collaboration and work-flow
In most industries, collaboration around AI and ML is not easy for designers, given the fact that experienced data scientists or AI experts are hard to come by, or they are not part of the teams (Yang, 2018). This is reflected in the designers' lack of understanding of the technologies, but also in the work-flow around these technologies (Dove et al., 2018).
Moreover, due to the lack of understanding of the technology — as mentioned above — designers are rarely leading the ideation process (Dove et al., 2017). Yang (2018) suggests that machine learning is not part of a user-centred design process, due to the designers' lack of tools and patterns that could support changes over time. This leads to designers being involved too late in the development process, missing many opportunities to generate novel applications with the technology (Yang, 2018).

d) Education
Thirdly, university education does not prepare designers well for these challenges. Considering that interaction and UX designers should the best fitted for the job, it is quite striking that the topic is missing from major textbooks (Preece, 2016; Cooper, 2014; Dove et al., 2017). Furthermore, from the fifty-one UX design respondents in Dove's et al. (2017) survey, only three mentioned they had taken a university course that prepared them for dealing with AI / ML.

2.4 Summary and conclusion
We have so far discussed the first crisis introduced in the design field by new material developments, which called for new theoretical and practical structures to face the challenges. In the following years after Manzini's seminal work, fast developments in information and communication technologies drove most industries into the information age's revolution. Suddenly, product and service development was forced to deal with the rapid changes in the digital age, and designers began to specialise in fields such as interaction and interface design. To cope with the new digital materials, design researchers began to experiment with technologies such as Bluetooth, motion sensors, etc. They aimed to understand the new digital materials better and incorporate them into the design practice so that new applications could be discovered and revealed. However, in the last ten years, a new set of technologies gained traction and moved into the global market: "big data" and different subsets of artificial intelligence such as machine learning.

These new technologies have different characteristics than previous ones. They require exponentially more resources in terms of computational power, datasets, and infrastructure. They are also highly complex and introduce challenges like data privacy and security. Their rapid integration into everyday products and services, means designers are expected to work and innovate with them in the near future (Dove et al., 2017). However, the challenges of working with big data, AI and connected products go beyond

HCI, as, e.g. service and industrial designers are already facing them (Bergström, 2010). It is clear from the literature that in the UX and HCI community there has been a fast-growing interest in the topics of "big data", IoT and AI/ML. However, research on these topics in design areas further away from computer science is not as pervasive. Therefore, the research questions (1.3) are aimed at opening up the discussion to the broader design community. This was done following the argument that just as previous technologies like digital interfaces and mobile technology were first a topic of interest for HCI and interaction design, now their ubiquity demands all kinds of designers to develop frameworks to work with them. Also, as we have seen in the literature, "big data" and the new data processing technologies are increasingly becoming part of our social fabric.

As seen in the literature, designers face new and complex problems when dealing with "big data" and new data processing technologies. The challenges have been outlined earlier, and can be summarised as a) understanding the technologies, b) prototyping with them, c) collaboration around the technologies and introducing them into the design workflow, and finally d) educating designers on this topic. These findings partially contribute to answering the first and second research questions, but will be explored further in chapter 4 when presenting the case study and later in chapter 5 in the final discussion and reflection on the practice.

In regards to the third research question — how the designer can cope with the aforementioned technologies —, the literature does not provide one single clear answer. However, it does call for designers to develop a "kind of abstraction that focuses on the match of contextual capability and user value; a kind of taxonomy that is likely to be radically different from ones used by data scientists" (Yang, 2018). This resonates with Manzini's work, whom in his analysis on how other disciplines were coping with new materials described how engineering had abstracted and codified knowledge. Engineering did it in order to adapt to the rate of change in material development (Manzini, 1989, p. 53). Manzini at the time recognised that designers were traditionally able to learn about materials through theory and practice, but because of the rapid pace in technological development, the only possible way for designers to grasp new material concepts was through theoretical abstractions (Manzini, 1989, p. 53, Bergström et al., 2010).

To conclude, the literature highlights that the challenges are indeed new for designers working with "big data" related technologies. Furthermore, traditional design practice and research are not in their current state mature enough to deal with the complexities of these new technologies. It is in this context that the research through design practice will be presented with the aim of digging deeper into the first two research questions and opening the discussion on the possible solutions designers can explore.

3. Methods

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3.1.1 Research through design

In order to answer the research questions, this thesis utilises a research through design approach. Research through design (RtD), as defined by Zimmerman, Forlizzi and Evenson (2007), is a way of conducting scholarly research using the design practice to generate new knowledge (Zimmerman and Frolizzi, 2014). There are two main differences between research through design and regular design practice. First, RtD intends to generate new knowledge instead of creating a commercial product. In other words, "design researchers focus on making the right things, while design practitioners focus on making commercially successful things" (Zimmerman, Forlizzi and Evenson, 2007). Second, the contributions should display an important level of novelty. These can be novel integrations of theory, technology, user need and context. From this perspective, one of the important contributions of design theory is in "making accessible the kinds of decisions and rationales that comprise an artefact's embodied theory, or give dimensionality to its design space" (Gaver, 2012).

Zimmerman and Forlizzi (2014) see RtD as an answer to an early days HCI challenge, in which the *thing* proceeds *theory*, instead of theory driving the generation of new things. As Carroll and Kellogg (1989) had pointed out, the computer mouse needed to be developed before research could be done to show it was a good design. Therefore, RtD encourages researchers to become active constructors of the world they ambition, by introducing new *things* to the field, and having these new *things* be informed by current theory. Thereby producing a dialogue between "what is and what might be" (Zimmerman and Forlizzi, 2014).

Therefore, this thesis' goals are closely related to RtD. First, this thesis aims to understand the challenges of designers working with large data sets and their related technologies. As the literature points out (see 2.5), this is a novel problem for design researchers and practitioners. Moreover, the context and scope of the design project carried out for Vattenfall had an exploratory approach, deemphasising aspects such as "the detailed economics associated with manufacturability and distribution, the integration of the product into a product line, the effect of the product on a company's identity, etc." (Zimmerman, Forlizzi, Evenson, 2007). The research questions concentrate on one particular aspect of the design process. Namely, the early ideation stage and the exploration of data as a material from a design perspective. In the next section, details regarding the framing of the project will be introduced to define the data requisites.

3.1.2 Framing design research and practice

Framing the design practice within a RtD framework requires certain methodological aspects to be considered. According to Reeker et al. (2016), these are: a) the type of design project, b) the moments of interaction, c) documentation, d) development of artefacts and e) generation of insights. First, the type of design project needs to be described, with its different phases, to provide a clear understanding of what design outcomes are expected. Second, the moments of interaction with other people relevant to the research need to be captured. The reason behind it is that project stakeholders or team members affect the design process and the research itself. Third, a rigorous documentation of the design process needs to be gathered (Zimmerman, Stolterman and Forlizzi, 2010), including "both the documentation of the evolution of the design artefact itself, and the documentation of the development of research insights through the design exercise." (Reeker, Langen and Brazier, 2016). Subsequently, the development of the design artefact needs to be properly documented, with the changes it undergoes over time, together with the motives that drive those changes. And finally, a description is needed of the "dynamics of the development of the research insights" to answer the research questions (Reeker, Langen and Brazier, 2016).

Within the now defined RtD framework, this thesis aims to answer the three main research questions by presenting a design project done for the energy company Vattenfall. The six-month design practice was used as an opportunity to explore different research questions. Originally, the design brief agreed with Vattenfall read: "to analyse the current state of Vattenfall's user data and combine it with external data through a design process, to generate new possibilities regarding services and business models". The broad scope of the brief allowed me to explore different aspects of the design process of working with data and data related technologies that I thought were relevant for the practice and theory of design (see 2.5). I approached the design practice and my research with the goal of learning about the relationship between design and a new digital material.

Recapitulating the research questions: RQ1: What challenges are designers facing when working with "big data" in a data-rich industrial context? RQ2: How is working with "big data" and new data collecting and processing technologies different from other design materials? RQ3: How can designers overcome some of the challenges of working with data? — In order to answer these research questions within the RtD framework previously presented, this thesis' requirements in regards to the design practice, data collection and analysis are framed as follows:

- The type of design project is the early conceptual stage of a design practice within an industrial context. In this context, the designer develops different concepts to produce knowledge about how to work with data as a design material. The designer is part of a product development team, but works individually on the brief, communicating with the team and other stakeholders within the organisation. The scope of the practice is to go from ideation to concept development, without considering possible business models, branding, production, distribution and integration with other Vattenfall products.
- Giving the research questions, the type of design knowledge produced is not only within the design concepts themselves, but with the emerging new processes used during the practice. In other words, what the designer does in order to be able to use data as a design material, and not just the artefact themselves. As seen in figure 3.1, the design process is an area of focus throughout the design practice, supporting the design of the different concepts. Focusing on both the design process and the outcomes is critical especially when answering RQ 2 and 3.
- Due to the importance of the industrial context for the design practice when working with data as a design material, as stated in RQ1, a description of the interactions between the designer, the product team and stakeholders within the organisation are captured to provide details to the practice's context. Due to the complexity of the new data related technologies (see 2.4), collaboration with members of the organisation is of great importance, together with the way the organisation is structured to enable design achieve its goals.
- Changes in the chronological development of different design concepts are documented, along with changes in the design process. The interaction between design process

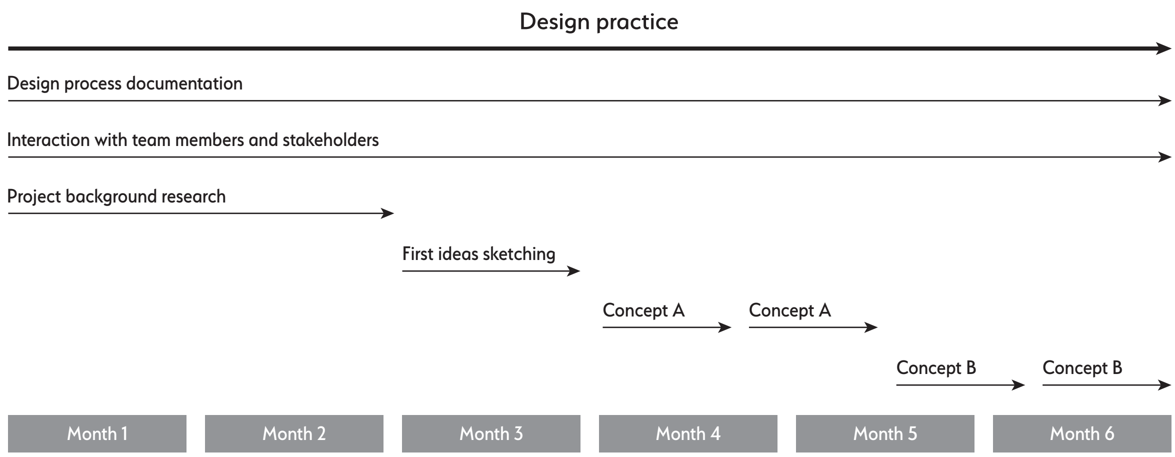

Figure 3.1. Design practice data collection.

development and advancements of design concepts and sketches is of great importance when addressing all the research questions.

Because the design project was commissioned by a private company (Vattenfall) and a non-disclosure agreement was signed between the parties, the stakeholders and team members will remain anonymous. Moreover, internal discussions regarding the company's data, IT architecture, product roadmaps, customer data structures, etc., had to be removed from the records. Internal documents that contained customer research, privacy sensitive files, classified material and internal memos were only accessible through Vattenfall's computers, and are not possible or retrieve any longer.

3.1.3 Data collection

Data was collected throughout the design practice, of which all can be categorised as qualitative data. Different data collecting methods were used and are detailed below; however, the overall structure and categorisation of the data were done retrospectively, according to the framework presented in 3.1.2. Thus, the three categories are: *design process*, *design concepts*, and *interaction with team and stakeholders*.

3.1.3.1 Design process

Data collection to capture the design process was done throughout the practice, from the early stages of the project until its completion. Collecting and analysing design process data was done with the goal of exploring the new challenges that designing with data presents for the design practice. Notes were taken specifically with the purpose of describing the different ideas and frameworks I used when working with data as a material. The primary data source was the design process notes: a physical and digital diary where I wrote down and sketched the different steps of my process. The focus of the notes was on how to visualise, combine, categorise and abstract the data to explore its different properties and possibilities. Additionally, the notes were meant to reflect on the challenges of the new material and how it affected the traditional design process and methods. Each entry had a date and was structured chronologically (see table 3.1 for more details).

Source	Method	Date
	Design process	
Internal reports	2 reports on product strategy	2015
Customer data	More than 40 variables. Accessed through Vattenfall's computers	2015
Customer research	3 reports on product development customer research	2015, July 6
Framework brainstorm	Physical notes and sketches	2015
Design process notes	Compiled after the final presentation. ~40.000 characters from digital notes and 8 diagrams	2016, January 15
Final report	18 page report	2016, February 2
Reading list	84 chronological entries on online articles read	2015, Mar - 2016, Dec
	Design concepts	
Prototypes / sketches	10 pages of paper sketches. ~20 digital prototypes	2015, Sep-Dec
Design notes	More than 20 entries and 30 sketches in paper and digital format	2015, July-Dec
	Interaction with team members and stakeholders	
Data Scientist A	2 theme interviews, 1 hour each	2015, October 21 2015, November 19
Data Scientist B	1 theme interview, 1 hour	2015, October 21
Energy expert and data scientist	1 group interview, 1 hour	2015, July 30
Energy expert	2 theme interviews, 1 hour each	2015, June 29 2015, November 18
Mid-term presentation feedback	2 interviews, 1.5 hours each	2015
Product developer A	1 interview, 1 hour	2015, July 19
Designer A	1 theme interview, 1 hour	2016, January
E-mail communication	~60 grouped e-mail discussions. 5 key e-mail discussions used	2015, Jun-Dec

Table 3.1. Data sources and methods.

Internal reports produced by Vattenfall, the final report presented to Vattenfall, and a reading list are also helpful sources to provide further details into the design process. The internal reports were integrated into the early stages of the design process, as some of them contained product strategy and customer research that was done previously by Vattenfall. This helped create the foundation for the practice. The final report contains a description of the design process that was given to Vatenfall after the final presentation, which includes sources and a bibliography; some of these around the topic of working with data. Moreover, the reading list follows the non-academic readings done during the practice, and present a chronological description of practice related readings that were at times incorporated into the design process. Finally, notes on a data framework workshop and the customer data were used to provide details on how a particular data source (customer data) was used and tried to be incorporated into the design concepts. Customer data presented a clear challenge for the design process, and therefore its structure and variables will be presented.

3.1.3.2 Design concepts

An important aspect to be considered when answering the research questions is the design artefacts themselves, since they provide a definite and tangible result of design practice when incorporating different data sources. Design concepts' documentation needs to show not only the design artefact itself but the decisions behind them. Therefore, the data collected during the practice was divided into two. First, a collection of sketches and prototypes were collected in both paper and digital format. These are direct results of the practice and show how the designer was incorporating different data sources into one final product idea. Additionally, design notes were also collected. These were digital and paper entries in a diary, where rough sketches had notations describing the rationale behind the decision making. These were not tightly structured, following an open design ideation process of testing different ideas over and over again. Both data sources in combination with the *design process* data collected provide insights into the internal design process and the external conversation with the materials.

3.1.3.3 Interaction with team and stakeholders

As stated earlier, interactions with people that are relevant to the design practice are fundamental when doing RtD. Since the first research question directly addresses the importance of the data-rich context in the design practice, this research area is of particular focus for the thesis. Moreover, working with data and its related technologies is not only a new technological context for the designer, but also for some organisation. More and more companies are using large data sets they collect every second together with external data sources to optimise and create systems, processes, products and services (see 2.1.2). Therefore, collecting data to contextualise the design practice in a particular industrial context is of great importance to understand the limitations and opportunities the context presents. To provide a detailed understanding of the organisational context and the communication with the team and other stakeholders, different methods were used to gather data.

Firstly, eight interviews with internal stakeholders and team members were held during and after the design practice. Each interview lasted for approximately one hour. The interviewees consisted of two data scientists, a designer, an energy expert, a product developer and a product manager. The initial interviews were done with the energy expert and product developer with the intention of understanding Vattenfall's approach to data-driven products and the role a designer could take within the company. These were semi-structured interviews, allowing for changes in the questions and style to accommodate to the research stage and the context if needed. The later interviews with data scientists and designers followed a different plan, more in tune with the research questions of this thesis. These were also semi-structured, but following a different theme, namely, processes and ways of working with "big data" within the product development team. A number of informal interviews were also held on a weekly and sometimes monthly basis with different members of the organisation as well.

E-mail records containing communication with internal employees during a one-year period were gathered; before, throughout and after the project conclusion. These interactions with the team and stakeholders are of great importance as discussions can be traced back chronologically. Moreover, as each Vattenfall employee is provided with a code tag attached to their email address, it is possible to know which department they work for and what are their roles. Since e-mail is the most common way of communication between Vattenfall employees, e-mail records provide substantial insights into the interaction between the designer and the organisation.

Finally, given the nature of the design project, participatory observation was an important aspect of the data collection. Because of Vatenfall's size as a company (20.000+ employees), in the initial stage of the project, participatory observation was a helpful approach to understand Vattenfall's organisational structure, roles and culture in the organisation, departments' responsibilities and work-flow. Together with other internal documents such as organisational charts, participatory observation proved a valuable data collection method to contextualise the case. The observations were gathered digitally as a diary. Notes were taken mostly during meetings and presentations within the organisation.

4. Design practice

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4.1 Background and brief

Founded in 1909, Vattenfall is a leading European energy company with over 6 million electricity customers, 2 million heat customers and 2.3 million gas customers. They operate in Sweden, Germany, The Netherlands, Denmark, the UK and Finland, with their headquarters in Solna, Sweden. At the end of 2017, Vattenfall employed over 20.000 full-time workers.

During the year 2014, together with four other design colleagues, I participated in a project through Aalto University to re-design one of Vattenfall's products (Energy Watch). The project was finalised and presented in December 2014. A few months later, early in 2015, I contacted our Vattenfall supervisor in the previous project with the intention of collaborating further in the future. The supervisor, a senior product manager working in the Finnish offices of Vattenfall, proposed me to work for six months during 2015 as a thesis worker. After discussing back and forth the topic of the thesis, we agreed on the design brief that I was to develop in six months during 2015, starting in June 1st and presenting the results in December or January.

Due to my previous experience with Vattenfall in 2014, I had a certain degree of knowledge of product development in the utilities sector, user behaviour, preferences and pain points of using energy-related products and general customer problems of utilities' users. Moreover, I had at the time three years of experience as a user experience and user interface designer, something that also influenced my decision of working with new technologies and digital interfaces. Furthermore, my Vattenfall supervisor's and my interest in "big data" related topics shaped the design brief in the direction of these new technologies and opportunities.

It is worth noting that Vattenfall's interest in the topic of "big data" and energy products and services was at the time growing exponentially. The organisation had recently created a new department to focus on customer-facing digital development, and the first few data scientists were being hired. In one of my first meeting with a data scientist, she stated "to my knowledge, there are only two other data scientists sitting in Sweden, so that makes three of us in the organisation" (Data Scientist A, personal communication, October 21, 2015). In this light, my supervisor wanted me to work on potential innovative solutions for the customers using the available data. I would join the product development team in Finland, a branch of the central Swedish product development department. After gaining approval from the department's manager, the brief was written as follows:

"Integrate external data, customer data and smart metering data to develop new product or service concepts".

While the design brief was somewhat general, the reason behind it was that Vattenfall did not have a clear product strategy to work with external data, open data or "big data". Their interest in having a designer working in the organisation was to seek out to "innovative business models being pursued around the world to identify new approaches to the smart home market" (Internal report A, October 5, 2015). Therefore, the brief's exploratory nature coincided with Vattenfall's early stages of digitalisation efforts. We agreed on using the brief as a framework for what technologies to use, and where to set the focus of my design efforts. However, I would later re-design the brief to focus on specific customer problems once I had gathered enough user research information.

4.2 Planning and research

Firstly, I set out to understand user and business requirements early on. Before the project had started, I collected material from the previous project I had done for Vatenfall with the intention of reviewing user research done with the team. Additionally, I collected articles on utilities' user research done by other energy companies and consultancy firms' like Opower and Accenture. The user research was later compiled in the final report presented to Vattenfall in early 2016. (Final Report, February 2, 2016). After I was given access to Vattenfall computers on the 1st of June, I also used internal documentation on user personas (Internal report on personas, June 1, 2015). This gave me a good understanding of the user types, needs, goals and behaviour to use as a first base before moving into the requirements phase. I had personally done research on context analysis for energy products before; therefore I also used that material.

Starting on June 1st, I started going to Vattenfall's offices. This allowed me to meet members of the Finnish product development team, stakeholders, and data scientist working for the customer insights department. In this context, I use the word *stakeholder* to refer to any Vattenfall employee that interacts and influences the product development team, but does not work under the same department. I used the organisational charts and the intra-net to have an overview of how teams were structured and how they collaborated.

Under my supervisor's team, there was no shortage of information regarding customers, their needs, problems with the current Vattenfall products and interactions with customer service (Energy expert, e-mail communication, January 1, 2016). Moreover, I could meet and interview Vattenfall users if I needed to, by requesting it to my supervisor and having management approval.

I had a few informal meetings with product developers and stakeholders to get to know the business requirements better. While there was user research available, I wanted to know what were the main problems the business was facing, and what was the product development department trying to do to solve them. During an early meeting with a product developer (Product developer A, July 19, 2015), I got to understand better issues like forecasting, grid optimisation, new data hubs that were being built in Europe, and new demand response solutions that were being tested. A few days later that month, I interviewed an energy expert and got valuable insights about existing solutions within Vattenfall to provide customers with advice on their energy consumption (Energy expert and data scientist, personal communication, July 30, 2015). This gave me a general overview and a direction to start developing the first ideas and to re-design the brief.

After collecting and analysing both user research and business needs information, together with my supervisor and consulting the product team I decided to re-design the brief to focus on two different areas. This allowed me to a) concentrate on two of the most critical customer problems, based on the existing user research, b) still use the original brief as a technological framework, c) tackle two key areas for the business. Thus, within the context of "big data" and new processing technologies, the brief now read:

a) Assist users to reduce consumption and achieve sustainability goals
b) Visualise and increase the user's understanding of their energy usage.

4.3.1 Working with data

After the brief was re-framed to focus on the user needs in the context of "big data", I started investigating and working on ideas that used different data sources in addition to metering data to address points a) and b) of the brief. In previous interaction design experiences, I would have started sketching at this stage, but the technological aspect still had too many open-ended questions. I kept reading on the subject of artificial intelligence, machine learning, "big data" and energy-related products (Reading list, March 29, 2015). An earlier meeting with my Vattenfall supervisor and product developers (Stakeholder meeting, May 2015) gave me a list of different solutions already in the market to investigate (Bidgely, Greenely, OPower, Simple energy, AlertMe; see table 4.1). I also met with software companies that collaborated with Vattenfall to see what technologies and solutions they had to offer that could contribute to advancing the brief (Vendor meeting, July 1, 2015; Supervisor, e-mail communication, July 7, 2015). However, the way to bridge the gap between the user needs and utilising Vattenfall's data in combination with external data to do so, was yet not very clear. After the meeting with a software vendor, the notes on the meeting read "it is clear that even new tech-oriented digital native companies have little to offer to energy companies, mostly because they do not understand their context, data or what their users needs are" (Vendor meeting notes, July 1, 2015).

Analysis of existing solutions						
Company	**Value proposition**	**Market segment**	**Revenue /y**	**Users**	**Features**	**Founded**
OPower	Opower is the world's leading provider of customer engagement solutions for the utility industry	B2B Utilities	$ 152M	< 100 (B2B) 60M (B2C)	Social proof Personalised insights Forecasting Disaggregation	2007
Greenely	Gree app to reduce energy consumption, free hardware	B2C Electricity consumers	< $ 1M	-	Personalised insights Social proof	2014
Bidgely	Energy monitoring and management solution for eco-friendly energy saving	B2C Electricity consumers	$ 3M	< 100M	Disaggregation Personalised insights	2010
Simple Energy	Motivate people to save energy and fundamentally change how "energy" and people engage	B2B Utilities	$ 25M	< 25M	Personalised insights and offers	2011
AlertMe	Smart energy and home monitoring system that enables users to control home appliances and devices	B2C Electricity consumers	$ 20M	500 000	IoT platform Automation Analytics	2006

Table 4.1. Existing solutions in the market.

After communicating with the only data scientists available in the organisation and stakeholders working in customer insights and online sales, it became clear that data experts' main and single role in the organisation at that stage was to create models for customer churn prediction and other marketing purposes (Data Scientist A, personal communication, October 21, 2015; Data Scientist B, personal communication, October 21, 2015). Moreover, data scientists did not have access to consumption data, only customer data and external customer data bought from other private companies (Data Scientist A, personal communication, October 21, 2015).

4.3.2 Collaboration and data

Throughout the project, communication and collaboration between product development and data scientists were sporadic. I was the only member of the product development team that met with data scientists on a weekly or monthly basis. As for the data scientist working in the Finnish offices, her tasks were assigned from "a selling point of view and customer communication point of view" (Data Scientist A, personal communication, November 19, 2015). I had the opportunity to meet with the data scientists by booking appointments, but we had no recurrent meetings or alignment between the departments. On occasions, I had to meet external machine learning experts to discuss ideas and possible implementations (Supervisor, June 15, 2015, e-mail communication).

There was a lack of coordination and alignment when it came to working with data in the organisation, as one data scientist put it, there was "no central coordination to get the data we want; that would be perfect" (Energy expert and data scientist, personal communication, July 30, 2015). Each department was given access to a particular data set, for example, customer service and customer insights had access to customer data, integration and support to consumption data, etc. In order to discuss issues from a customer need point of view, one had to plan meetings in advance that would bring a member of each team that dealt with one particular data point connected the customer and run a long session together. To run such sessions, one had to have management approval from each department.

As a result, I had to research and read on my own about possible ways of using “big data” and new collecting and processing technologies and then arrange a meeting with the developers or data scientist and discuss about the ideas and their feasibility (Reading list, March 29, 2015; Energy expert and data scientist, personal communication, July 30, 2015). Furthermore, I spent much time gathering material about other products that integrated technologies like IoT and artificial intelligence to find inspiration and start producing the first concepts (Reading list, March 29, 2015; Design notes, July 6, 2015)

4.4 Framework for data classification

In order to generate a structured rationale to make sense of the data, I started to categorise internal and external data. Thus creating a kind of inventory of the available data that Vattenfall produced, data that they bought from third parties, and open available data. The goal was to understand what data was available, what other data it was linked to, which department was responsible for using it and how accurate it was. I thought this could help me find new ways of combining, processing and integrating the data into products or services that could solve one of the customer problems described in the brief (Notes on data types, September 11, 2015).

There was, at the time, no single framework for categorising and inventorising all the available data in the organisation (Energy expert and data scientist, personal communication, July 30, 2015), nor could I find anything in the general literature (Reading list, March 29, 2015). Therefore I created the categories based on what I required as a designer to be able to understand and use the data. As illustrated in table 4.2, the idea of categorising the data was to generate an inventory to visualise and track all available data, with the possibility of expanding the list and adding open data, third party data, etc. For me to understand only one type of data or even one variable, I had to contact different business units, request access and sometimes technical assistance (Data Scientist A, personal communication, October 21, 2015). Undoubtedly, this became a very time-consuming job, resulting in dozens of categories, sources, types and data formats. Consumer data alone had over forty variables (Customer data records, 2015, Vattenfall), and consumption data had dozens of variables depending on the contract type and product.

After a few weeks of trying to categorise the data and create an exhaustive inventory, I realised that job alone would probably take me months (Design process notes, January 15th, 2016). Understanding only one category of data was taking me days if not weeks, depending on its complexity. Moreover, once I understood and categorised one type of data, it did not make it easier for me to understand the next one. In other words, customer data collection, storage and processing was completely different from metering data. From security to architecture and application, there was very little knowledge that could be extrapolated from one dataset to another, at least from a design perspec-

Data categorization (anonymised version)				
Type	**Variables**	**Usage**	**Connected to**	**Accuracy**
Customer data (internal)	Contract number Customer number Contract type Place of delivery Contract starting date Contract end date Contact information Grid area Consumption estimate Customer service contacts ... more	*Department A* Internal application 1 Web application 1 Web application 2 *Deparment B* Service 1 Service 2	Campaign data Sales data Churn data Acquisition data ... more	Medium high
Customer data (external)	Estimated: Purchasing power Education level House type Household income Browsing behavior ... more	*Department C* Analytics CRM Campaigns	Campaign data Sales data Churn data Acquisition data ... more	Low
Metering data	Live to hourly Historical Temperature adjusted Aggregated consumption	*Department D* Web application 1 Web application 2 Mobile application 1	Production data Forecasting Spot price data ... more	Very high

Table 4.2. Data categorisation. Anonymised version.

tive (Notes on data types, September 11, 2015). What I needed was to understand at an abstract level what data was possible for me to use as a design material, to move into an ideation stage when I could further discuss possible design concepts with experts like data scientists or developers (Design process notes, January 15th, 2016). I wanted to find a framework that would allow me to think about data in a more abstract and general way, if I wanted to use data as a design tool to solve problems for the users (Notes on data types, September 11, 2015).

After discussing with data scientists about creating a lightweight framework to categorise data and reading further on the subject, I sketched different solutions (Notes on data types, September 11, 2015). Finally, I came across a report on ways to classify "big data" by the United Nations Economic Commission for Europe. I created a simplified framework with three classifications of "big data" based on the report and the book Designing Connected Products (Classification of Types of Big Data, n.d.; Rowland, 2015):

a) *Human-sourced information*: "this information is the record of human experiences, previously recorded in books and works of art, and later in photographs, audio and video. Human-sourced information is now almost entirely digitized and stored everywhere from personal computers to social networks. Data are loosely structured and often ungoverned"

b) *Process-mediated data*: “these processes record and monitor business events of interest, such as registering a customer, manufacturing a product, taking an order, etc. The process-mediated data thus collected is highly structured and includes transactions, reference tables and relationships, as well as the metadata that sets its context. Traditional business data is the vast majority of what IT managed and processed, in both operational and BI systems. Usually structured and stored in relational database systems”.

c) *Machine-generated data*: “derived from the phenomenal growth in the number of sensors and machines used to measure and record the events and situations in the physical world. The output of these sensors is machine-generated data, and from simple sensor records to complex computer logs, it is well structured. As sensors proliferate and data volumes grow, it is becoming an increasingly important component of the information stored and processed by many businesses. Its well-structured nature is suitable for computer processing, but its size and speed is beyond traditional approaches”. (Classification of Types of Big Data, n.d.)

The framework’s goal (see figure 4.1) was to allow me to concentrate primarily on user problems and use different data more intuitively, as a designer would typically do with other materials. Essentially, the main difference between the previously done data categorisation (see table 4.2) and the abstraction framework (see figure 4.1) was that the former required an in-depth knowledge of each data type even to begin to do design work, while the latter only requires a high level and abstracted awareness of what data is possible to collect/process.

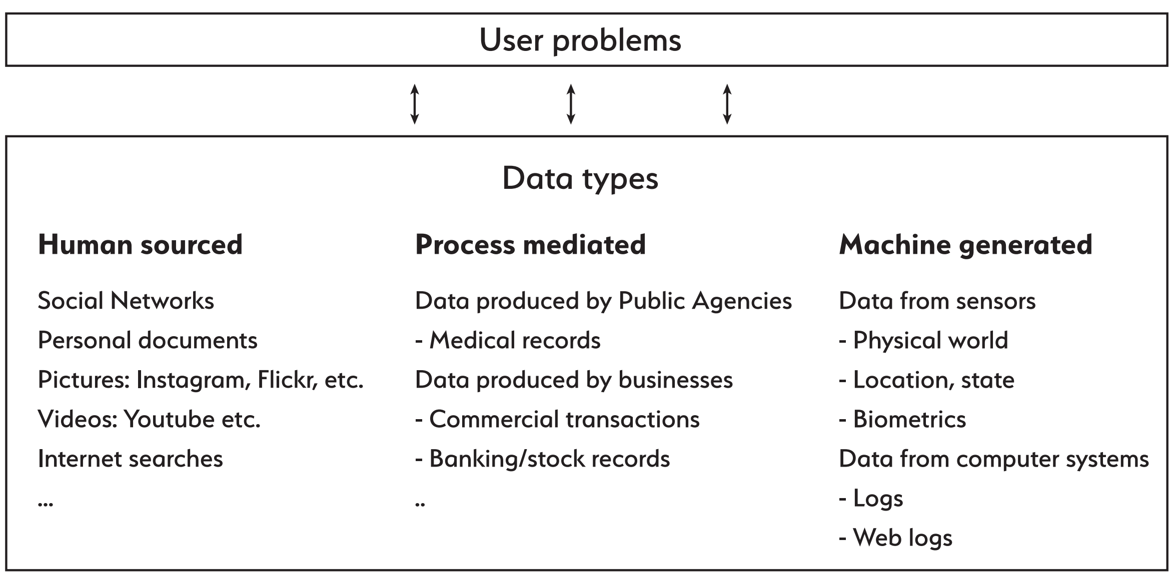

Figure 4.1. Data abstraction framework

The data abstraction framework was more a sense-making framework than a detailed description of each data classification together with its technical breakdown. Based on the re-design of the brief and my role as a designer, I was to primarily concentrate on two different customer problems, utilising Vattenfall’s data and external data as design materials. However, the main problem I found was to move from user problems to an ideation stage where data would be the main design material. Before I could start ideating around the user problems I was focusing on, I had to make sense of the existing data. Categorising the data (see table 4.2) provided no clear path from user problems to the ideation stage. Even after categorising different data types, once I started working on a user problem, I had to go into the technical details of each type of available data to analyse whether it was useful to solve the user problem or not. As a result, the first sketches were simple integrations of existing solutions already in the market that I had previously studied (see table 4.1)

Therefore, I decided to take the next step and focus on one of the user problems I had identified in the brief, and through the data abstraction framework generate different ideas that would use data in different and novel ways. This meant sketching possible solutions to the user problem while considering the following design materials: a) human-sourced data, b) process-mediated data and c) machine-generated data. I did this exercise on my own at first, to test whether it could help me to generate different ideas before involving a data scientist.

4.5 First concept: energy social hub

Almost three months had gone by when I first started sketching with a clear user problem in focus. I discussed with my supervisor to have a midterm presentation of the concepts so I could get feedback on the ideas produced before the final presentation (Supervisor, October 22, 2015, e-mail communication). Previous sketches an ideas had all been around how to conceptualise the data, understand it, communicate and collaborate with the data scientists.

The first attempt at using the framework to sketch a first solution was aimed at solving point a) of the brief: assisting users to reduce consumption and achieve sustainability goals. After going through the user research and analysing Vattenfall's existing products, I broke down the problem in four different areas that could bring value to the customer needs. These were: a) social norms, in order for the customer to reduce consumption based on comparing themselves with similar households, b) rewards systems to encourage customers to achieve sustainability goals, c) competitions to engage customers in reducing consumption through gamification, and d) personal advice and insights, to get the right information at the right time to consume energy more efficiently.

Once I had four possible areas for bringing value to the customer problem, I used the framework to ideate and sketch possible integrations or combinations of data that could solve the user problem. I did this without yet concentrating on the technical details of each data type, but while still having a high-level understanding of the properties of each data class in the framework (see figure 4.1). Following figure 4.2, I started at the top with the user problem I was trying to solve. Then moved one step below to the four areas I had identified that could contribute to solving the user problem in different ways. Afterwards, I sketched possible ideas on each area while reviewing the high-level possible data sources to use, always with enough abstraction to allow myself not to get stuck on technical details. At this stage, I used a red letter which referenced each of the four areas to mark the possible data sources to use in each of them (see figure 4.2). While doing this, I wrote down questions for myself and also for the later discussions with the data scientists (Framework brainstorm, n.d. Gaspar Mostafá).

The framework did not provide total clarity on how the data could be processed, where to access it, etc.; but it was a good start to have a conversation with the data scientists. The questions that came from using the framework were valuable to start going into details. For example, regarding point c) competitions, I wrote the following questions:
- "What parameters do we need (weather, heating system, historical consumption, household size, etc.);
- How can we process the data to categorise user profiles?
- Can we test user profiles against real data?
- How can we prototype a user profile with existing data?
- Can we auto-generate customer advice and assign them to profiles?" (Framework brainstorm, n.d. Gaspar Mostafá).

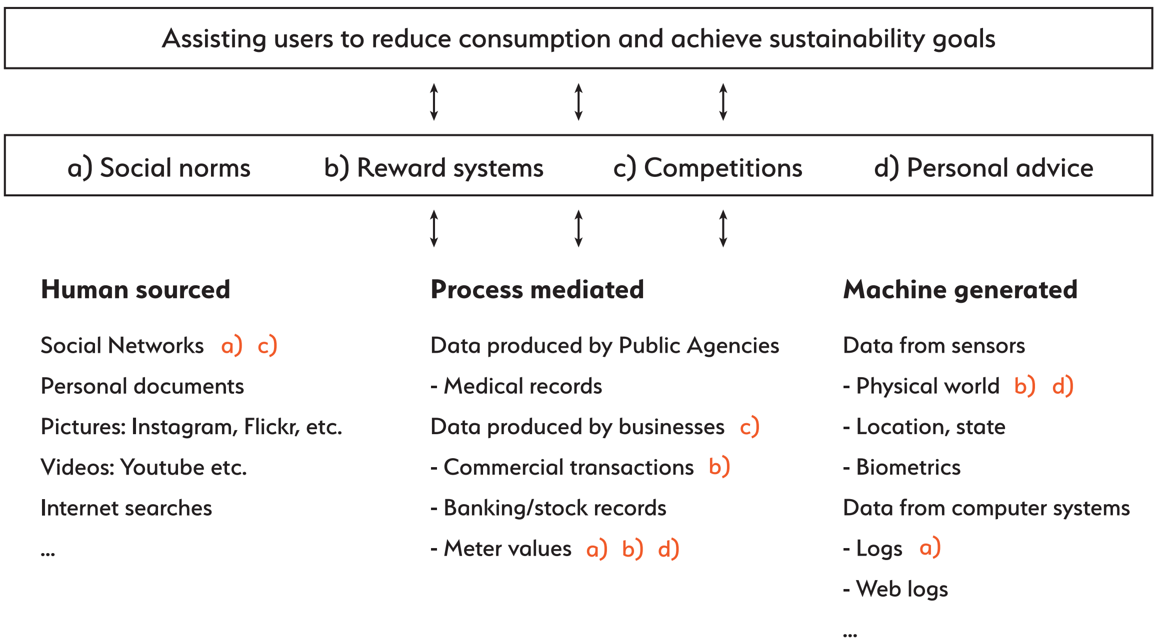

Figure 4.2. Data abstraction framework: energy social hub

These questions were reviewed and discussed with data scientists and through my readings to iterate on the concepts and have a more grounded assumption on the feasibility of the ideas (Framework brainstorm, n.d. Gaspar Mostafá).

I started to brainstorm about possible data sources and data processing methods that could contribute to each four identified areas. After a few rounds of iterations and with the assistance of a data scientist, the first concept of the product gained shape: an energy social hub for Vattenfall costumers. As mentioned earlier in this thesis (3.1.2), due to the non-disclosure agreement, I will not be able to describe the concept entirely. In short, the product combined multiple data sources to provide the customer with personalised advice on their consumption patterns, and a way for them to compare and compete against similar households. It served as a platform for customers to share information with similar profile households on how to reduce consumption (see figure 4.3).

Initial feedback from the product development team was very positive. There were at the time a few initiatives around the organisation that could use a digital platform to

Figure 4.3. Energy social hub, first sketches.

engage with customers in different areas, such as solar energy. Moreover, the concept of generating customer profiles based on their consumption patterns, heating systems, consumption response to weather, etc., was a new idea that the organisation saw as positive and interesting to pursue, not only for this project (Mid-term presentation feedback, n.d. 2015, personal communication). A short customer feedback session was organised with external users (Design process notes, January 15th, 2016, compiled after the final presentation). The input was incorporated into the second round of design sketches (see figure 4.4).

In retrospect, using the data abstraction framework proved to be valuable in some respects. First, it allowed me to test different ideas on my own, without having to depend on feedback or assistance from data scientists or developers. I could concentrate on a specific user problem, and ideate by thinking about data not in terms of technical properties, but abstracted as human-sourced, process-mediated and machine-generated. This gave me a certain degree of freedom to come up with new ideas, which I could later discuss with data scientists. Instead of discussing properties of a particular dataset (see table 4.2), I could present sketches or questions to data scientists and developers, pushing new design ideas forward instead of letting the discussions be technology driven only. Secondly, it also provided me with an interface for discussion. In other words, presenting the framework to data scientists, for example, helped me introduce the user problem I was trying to tackle and the possible areas of action, together with the possible data sources I was considering all at once.

However, a closer look at the concept (Energy Social Hub) in contrast with the existing products in the market that had been previously analysed in the project (see table 4.1) and the reading material provided by Vattenfall and my own (Design notes, July 6, 2015), there were clear shortcomings in the first attempt. The ideas incorporated into

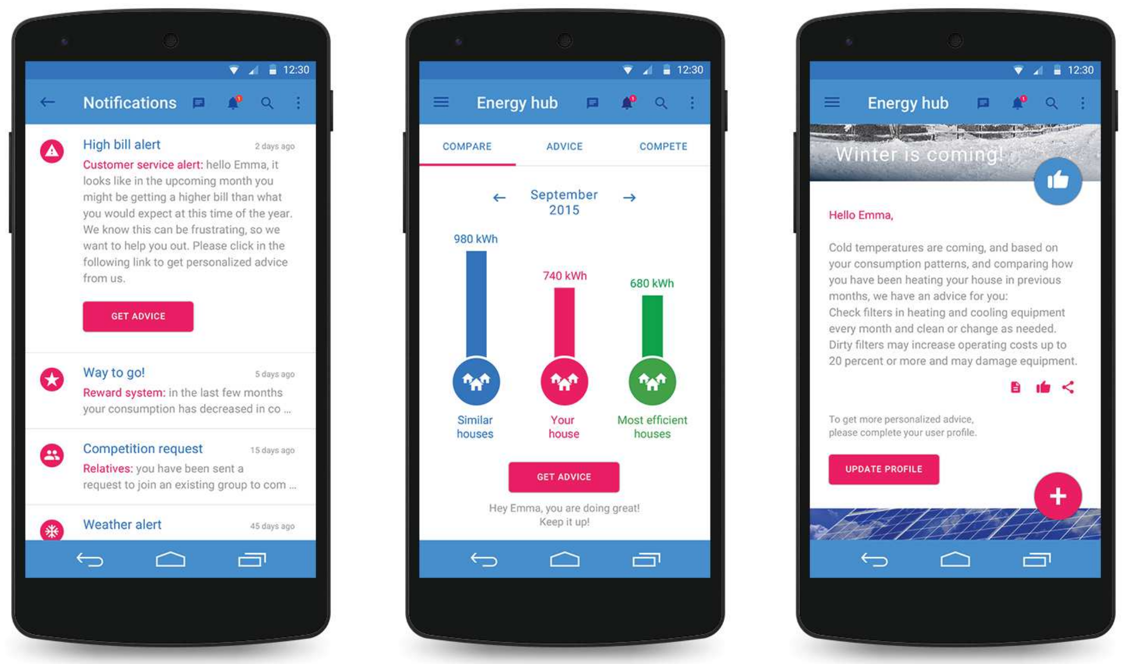

Figure 4.4. Energy social hub, second sketches.

the first sketches were recycled from existing products in the market (see table 4.1): namely, reminders, personalised insights, social proof, social media savings programs, etc. (Design notes, July 6, 2015). Even if there were sketching, brainstorming and design feedback sessions with different members of the organisation, the results did not differ from the existing and classic examples of utilities' consumer products incorporating data analytics.

4.6 Second concept: augmented reality appliance recognition

Processing the lessons learned from the first attempt, I began working on a different design concept, targeting the second item on the brief: b) Visualise and increase the user's understanding of their energy usage. I wanted to work on a completely different design concept altogether, to see if making some changes to the design process could produce a better outcome. One of the problems of the first attempt had been that the analysis and breakdown of the customer problem had incorporated existing ideas of products that were already in the market. Thus, the framework was already guiding the ideation and sketching phase in a particular direction. As a solution to the problem, I decided to use a metaphor to describe a possible solution instead of existing technical concepts (figure 4.5). The idea came from the early user research I had done, and from innovation techniques used by the product development team in other projects. While I previously would have used existing concepts such as "appliance recognition" or "energy visualisation" as ideas to explore (Design notes, July 6, 2015), this time I used "understanding by seeing" to incorporate it in the framework.

The question I was asking myself was how I could help the customer see and feel energy differently, beyond existing visualisation solutions. I wanted the customer to be in their context of use (their house or apartment) and have a tangible experience of electricity as a physical product (Design notes, July 6th, 2015). I departed from the previous process

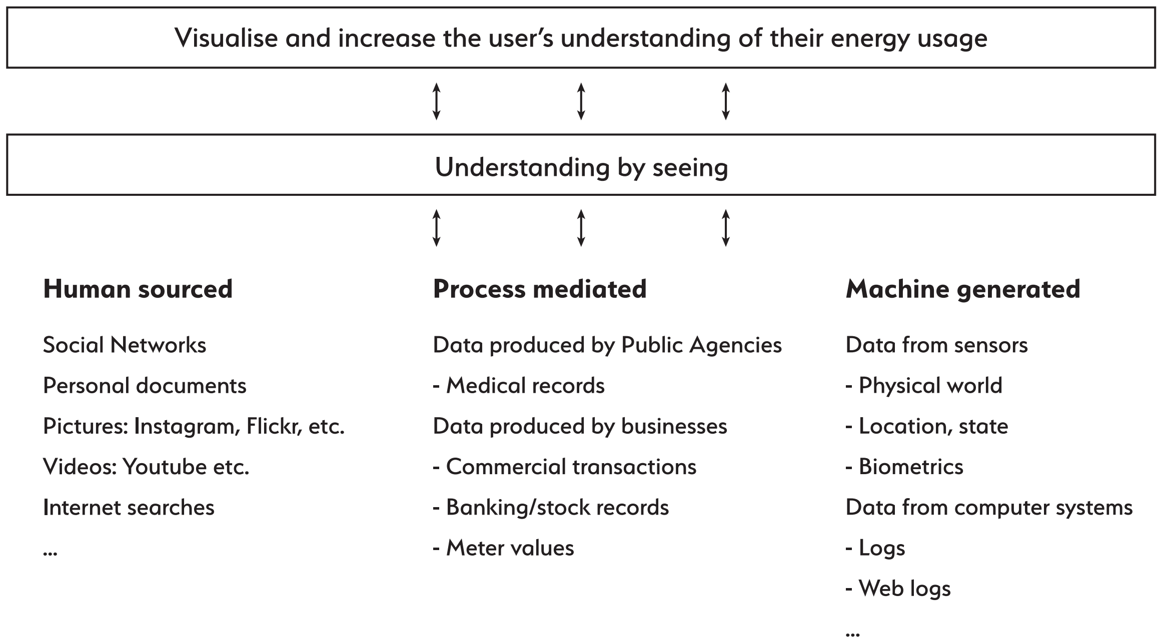

Figure 4.5. Data abstraction framework. Visualize energy.

(see figure 4.2) of identifying possible areas of action to solve the user problem. Those areas were already defining the possibilities of the product in the form of features or existing products in the market. In this second iteration working on a different concept, my goal was to explore different design ideas without the constraints of existing solutions or predefined requirements. By having a metaphor guide the design ideation process, my goal was to come up with novel ways of using and combining data and solve the user problem.

After a few sketching sessions and iterations without yet going into technical details, I began to explore the idea of an augmented reality application that when used, would show the consumption usage around the house for each appliance (Design notes, July 6, 2015). I explored a mobile application and other interaction concepts, but the most immersive one was augmented reality (see figure 4.6); it responded directly to the metaphor by allowing the users to see in real time how much each appliance was consuming, in terms of kWh or euros.

During a sketching session, I came up with a different approach for the framework to explore the idea further. I concentrated on the idea of seeing how energy worked, and for that, I needed to have a breakdown of each appliance's energy consumption. At the time, there was plenty of research on energy disaggregation and non-intrusive load monitoring; in other words, different techniques to recognise the electrical signature of each appliance and assign it a name or identifier (see figure 4.7). Depending on the resolution of the energy meter, the results varied from 60% and 70% accuracy to very low if the meter resolution was hourly or daily. Without the possibility to identify the consumption of each appliance directly from the meter without having to install smart plugs, the idea was going to be hard to implement. Therefore, I made use of the abstraction framework once again, this time focusing on how to find a way to see an appliance's consumption, searching for other ways besides the machine-generated consumption

Figure 4.6. Augmented reality appliance recognition. First sketch.

signature (see figure 4.7). What I had available, was the entire energy consumption for the household, and if the resolution was taken every one hour from the meter, there was not going to be a time-stamp consumption breakdown. Perhaps there was another way to collect the same information.

After a few rounds of sketching and informally discussing with the data scientist sitting in Finland, I started going one by one through the possible ways of knowing what appliances were in a particular household, without having to ask the customers for input. Using the framework, I went through possible data sources I could use to make each appliance visible for the user. As seen in figure 4.8, the data available was machine-generated and more specifically logs from computer systems. Therefore, I began to explore possible options in process-mediated and human-sourced data. In one of the rough sketches I did (see figure 4.9), I had the idea of using human-sourced information to have a breakdown of the appliances.
This could have been done in different ways, for example asking the users to click on different appliance icons, storing that data and using it together with the metering data. However, this required a lot of input from the customer side. Regardless, I kept ideating around the idea of collecting and processing human-sourced data in other ways.

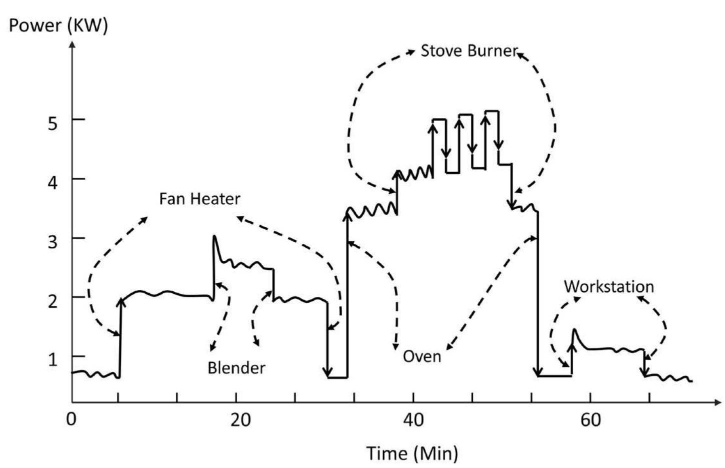

Figure 4.7. An aggregated load data obtained using single point of measurement. Zoah et al., 2012

Since the application was going to be used in mobile phones and tablets, I also had the possibility of

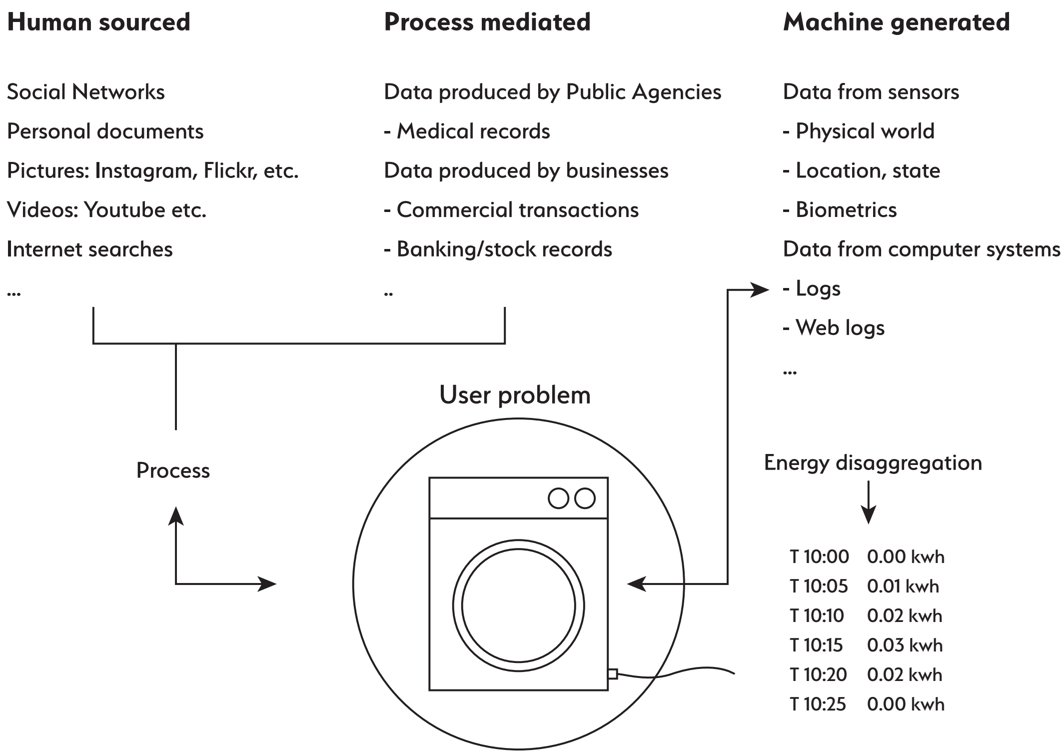

Figure 4.7. Data abstraction framework. Augmented reality appliance recognition.

using human sourced data like photos and videos. Therefore, there was the possibility of recognising the appliances with the phone/tablet camera. I discussed the topic with a machine learning expert who worked outside Vattenfall in image recognition technologies who explained to me what data was needed, how the system should be trained, etc. Furthermore, I also began researching on my own on the topic (Reading list, March 29, 2015).

At one point during my research, I found out about Clarifai, one of the winners of the ImageNet competition in 2014. They provided an online test of their image recognition services, where one could upload a photo and using their deep convolutional neural networks (a sub-field of machine learning, see 2.1.2), objects on the image would be recognised and tagged (figure 4.10). I tried several photos with different resolutions of kitchens, living rooms, bedrooms, and the accuracy was very high.

By using the phone/tablet camera, it was possible to recognise the different appliances in the household. To test the idea further, I produced a few sketches on how the application could look like, to test it with users and get feedback from the business. The feedback was very positive, and a few ideas like introducing heatmaps and consumption curves were incorporated

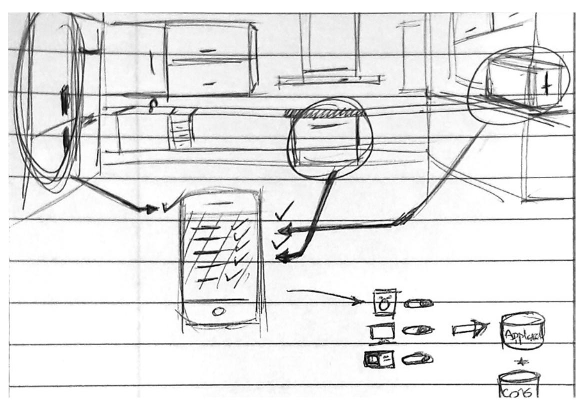

Figure 4.9 Augmented reality breakdown sketch.

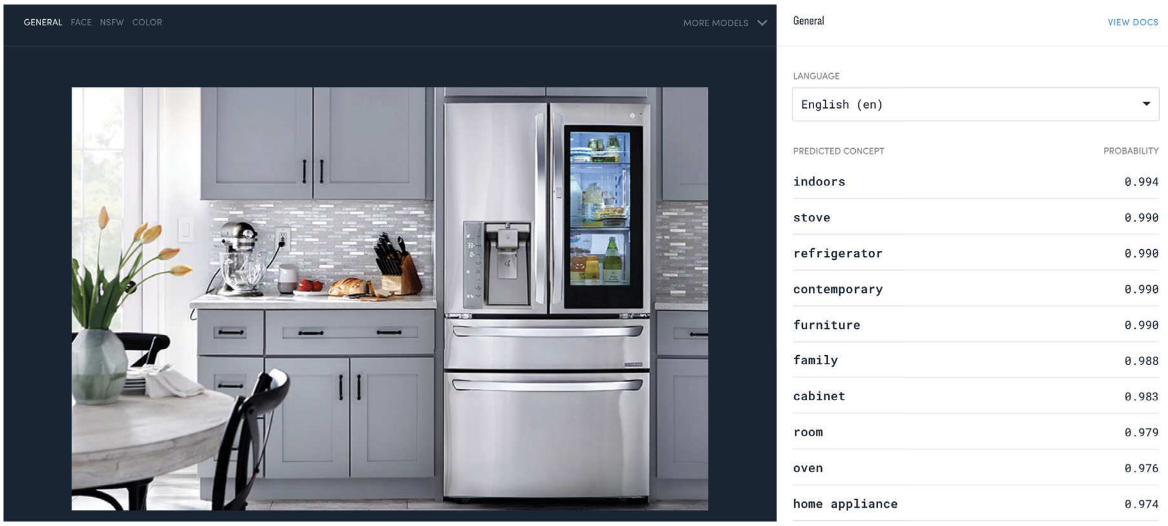

Figure 4.10. Clarifai, image recognition test.

into the final presentation. (Final presentation feedback, January 19, 2016, personal communication). Moreover, colleagues from research and development suggested that by only identifying a few appliances (the biggest ones), that could already make the appliance breakdown much easier (Final presentation feedback, January 19, 2016, personal communication).

Together with the team, we had discussions both in Finland and in Sweden regarding the feasibility of the solution and producing a minimum viable product to test with users. However, the lack of technical competence within the organisation in training deep learning models made it very hard to produce a minimum testable prototype. Moreover, at the time, we lacked the knowledge in the product development department to feed the appliance data into the energy consumption database to generate the appliance breakdown visualisation.

5. Analysis

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In this thesis, first a review of the existing literature has been presented, followed by a research through design project done in the utilities sector's industrial context. Consecutively in this section, the answers to the research questions will be summarized. Before that, a recapitulation of the research questions:

Research question 1: What challenges are designers facing when working with "big data" in a data rich industrial context?

Research question 2: How is working with "big data" and new data collecting and processing technologies different from other design materials?

Research question 3: How can designers overcome some of the challenges of working with data?

5.1 Answer to RQ1

Multiple challenges were identified in the design practice done for Vattenfall. From a material perspective, working with data presented multiple difficulties. In 2.2.2, it was stated that the traditional material view is that designers explore materials in a studio or a workshop, where they are used to shape, build and play with different elements; typically paper, wood, clay, etc., to develop tacit knowledge of what is possible (Buxton, 2007). Manzini had earlier identified that the new material advancements created a crisis in the traditional way designers interacted with materials. Both statements resonate profoundly with the design project presented in section 4.0 of this thesis. Firstly, the attempts to explore the materiality of data proved to be very hard. Referring to the categorisation and analysis of available data in Vattenfall, it was said: "Undoubtedly, this became a very time-consuming job, resulting in dozens of categories, sources, types and data formats." ... "once I understood and categorised one type of data, it did not make it easier for me to understand the next one. In other words, customer data collection, storage and processing was completely different from metering data" (section 4.4). The attempts at exploring the different properties of each dataset revealed that the level of complexity behind each set was too high to reveal any pattern of properties across a number of datasets (see 4.4). Not only the data itself was complex enough, but the fact that each type of data was collected, stored, analysed, used and integrated across applications in different ways only increased the difficulties to understand it and use it. This is a clear reflection of another finding in the literature (see 2.3), showing that one of the most prominent hardships designers face when working with new data processing technologies is their lack of understanding of what these can and cannot do (Holmquist, 2017; Carmona, Finley, & Li, 2018).

Due to the difficulty of understanding the properties of the available data and the different ways to process it, the transition between knowing the material and working with it became another challenge in the design process. "Categorising the data (see table 4.2) provided no clear path from user problems to ideation stage" ... "Even after categorising different data types, once I started working on a user problem, I had to go into the technical details of each type of available data to analyse whether it was useful to solve the user problem or not. As a result, the first sketches were simple integrations of existing solutions already in the market that I had previously studied" (section 4.4). These difficulties in transitioning from knowing the digital material to working with it can also be found in the literature. Ozenc et al. state that designers struggle to interact with digital materials like software and data because of their immateriality and intangibility (Ozenc et al., 2010). Yang (2018) mentions how innovation and prototyping are also a significant hurdle when working with these new technologies. This is reflected in the practice (see 4.4) by how much groundwork had to be done before producing design ideas that could be sketched. Moreover, as already stated, the first sketches were recycling existing ideas that were already in the market.

Regarding the exploration of data as a material, in section 2.2.2, the material approach in HCI was reviewed, which tries to tackle the problems of working with digital materials by creating 'quick and dirty', rough yet fully working sketches that make visible the different properties of a given material. In the practice presented in 4.0, it could have been possible to explore one type of data in particular. However, due to the nature of the brief, one of the goals of the design practice was to explore multiple data sources that could create new product and service opportunities for Vattenfall. Moreover, as mentioned above, extrapolating knowledge from analysing one single type of data into another type might prove problematic and wrong. Finally, even if one single type of data would have been the focus of this thesis, the speed at which these technologies are evolving can out-date that knowledge very quickly. Taking metering data as an example, in the last three years since this thesis' practice was carried out, there have already been significant changes in that technology alone: data warehousing provides new functionalities like caching for large datasets at B2B levels; cloud computing brings new analytics capabilities and at European level energy data hubs are underway (Data hub, 2018). According to Manzini, this problem breaks one of the conditions that allowed designers to set the relations between "conditions of use and performance that typified that material". That condition being: "Materials remained constant over time in terms of qualities and properties, and their variations (or the introduction of new materials) were slow enough to allow the adaptations of the system of meanings" (Manzini 1989, p. 32). This means that regardless of the effort undertaken by a designer to understand data as a material and set the "conditions of use and performance", only in a matter of months the technological context might leave that knowledge irrelevant.

An essential aspect of the first research question was the context of the practice. Understanding the design practice within the organisation provides insights into how dependent the designer is on the team, processes and organisational structure when working with "big data" and its related technologies.

During the early stages of the design project, the collaboration between the product development team and data scientists was problematic. "... it became clear that data experts' main and single role in the organisation at that stage was to create models for customer churn prediction and other marketing purposes" (section 4.3.1). Moreover, the data scientist had access to customer data only, and could not access metering data, for example. Since the product development team was mostly involved with energy consumption related products, the data scientists had very little knowledge of how they could help. In the literature, Yang (2018) mentions that one of the problems for collaborating around data related technologies is that experienced data scientists are not part of the product team, or are hard to come by at all. In section 4.3.2, it's further stated that "I was the only member of the product development team that met with data scientists on a weekly or monthly basis".
Furthermore, in 4.6 it is explained that the lack of technical competence within the organisation on training deep learning models made it very hard to produce a minimum testable prototype. Even if there was some communication with data scientists, the lack of alignment in terms of daily tasks made collaboration really hard and sporadic. Furthermore, at times "I had to meet external machine learning experts to discuss ideas and possible implementations" (section 4.3.2). This was a clear sign that the organisation lacked the steering of that kind of competence towards product development.

Another major challenge was the lack of central coordination of data related issues. As one data scientists put it, there was no "central coordination to get the data we want; that would be perfect" (Energy expert and data scientist, personal communication, July

30, 2015). Each department had access to a particular dataset, for example, customer insights had access to customer data, and no access to metering data. In order to work on projects from a customer perspective, "one had to plan meetings in advance that would bring a member of each team that dealt with one particular data point connected the customer and run a long session together. To run such sessions, one had to have management approval from each department" (section 4.3.2). As a result, two separate things happened. One, I had to bring different resources together, usually outside the product development department, and create a framework for aligning with data scientists and developers: "The framework did not provide total clarity on how the data would be processed, where to access it, etc.; but it was a good start to have a conversation with the data scientists". And second, to push the design process forward I had to spend a lot of time reading "about possible ways of using 'big data' and new collecting and processing technologies and then arrange a meeting with the developers or data scientist and discuss about the ideas and their feasibility" (Reading list, March 29, 2015; Energy expert and data scientist, personal communication, July 30, 2015).

5.2 Answer to RQ2

The review of the existing literature already provides an answer to this question. Regardless, this can be further substantiated by the evidence presented earlier the design project (see 4.0). Certainly, there is a clear difference between traditional materials and digital materials (see 2.2.1). However, even amongst digital materials, "big data" and its related technologies present a level of complexity that puts them in an altogether different category.

Firstly, categorising these new technologies is much harder to do than technologies such as Bluetooth or RFID (see 2.3). The data itself is complex enough, but additionally, the collection, storage, analysis, usage and integration across applications change over time from department to department and from team to team (see 4.4). As a result, the level of complexity and the material properties of this type of technology is always an amalgam of interconnected and interdependent components, which changes depending on a multiplicity of factors. Taking customer data as an example, only within Vattenfall that dataset has over forty variables, is used by different departments, processed by multiple applications and collected internally in combination with external sources (see 4.4). Moreover, it would also be fair to say that over a hundred employees, from customer service to customer sales, make use of that data in different ways. As a result, due to the multiple components that define the technology, the pace of technological progress affects its development exponentially. For example, while metering data collection remains (in certain areas) unchanged, fast developments in data analytics can create faster and more accurate consumption forecast.

Previously in the review of the existing literature, it was mentioned that one of the differences between "big data" related technologies and other digital materials such as Bluetooth or RDIF is that "the resources needed to work with, e.g. deep learning are exponentially larger (Yang, 2018)". This does also reflect on the design practice of this thesis, in two different ways. First, as already mentioned, the human resources needed to work with these technologies require alignment between different departments and competences. Something that in the context of Vattenfall was extremely time consuming and complicated due to the need for management approval. Also, secondly, the infrastructure to collect certain data like metering data, in combination with data warehousing, cloud computing and analytics, requires many resources even to use a small set of data to prototype an idea. While there have been improvements in some areas, like open access to appliance signature data, still the processing of the data and integration into a product does require a substantial investment of time and resources.

The evidence from this design research, therefore, indicates that not only is "big data" and its related technologies different from traditional design materials like wood or paper, but it is also different from other digital materials.

5.1 Answer to RQ3

It is not possible to give a straight and clear answer to the third research question. However, some general suggestions can be taken from analysing both the literature and the design practice. The literature calls for designers to develop a "kind of abstraction that focuses on the match of contextual capability and user value; a kind of taxonomy that is likely to be radically different from ones used by data scientists" (Yang, 2018). This resonates with Manzini's work, whom in his analysis on how other disciplines were coping with new materials described how engineering had abstracted and codified knowledge. Engineering did it in order to adapt to the rate of change in material development (Manzini, 1989, p. 53). Manzini at the time recognised that designers were traditionally able to learn about materials through theory and practice, but because of the rapid pace in technological development, the only possible way for designers to grasp new material concepts was through theoretical abstractions (Manzini, 1989, p. 53, Bergström et al., 2010). Moreover, Bergström states that new digital materials require the creation of concepts, to support "ways of understanding, describing and working" with them (Bergström et al., 2010).

In the design practice of this thesis, similar needs have also been identified. In the early stages of the design practice, a first attempt was made to inventorise and classify the different properties of different datasets. The goal behind this first attempt at categorising the data was "to understand what data was available, what other data it was linked to, which department was responsible for using it, how accurate it was, etc." (section 4.4). In Manzini's view, this could be categorised as the traditional design approach to materials, asking the question "what is it?". Unsurprisingly, there were clear shortcomings in approaching "big data" and its related technologies this way. First, "for me to understand only one type of data or even one variable, I had to contact different business units, request access and sometimes technical assistance" ... "Understanding only one category of data was taking me days if not weeks, depending on its complexity" (section 4.4). Trying to ask the question "what is it?" led to different obstacles. From lack of technical knowledge to security issues, to having to contact different resources across the organisation. Furthermore, it was also mentioned that "once I understood and categorised one type of data, it did not make it easier for me to understand the next one" (section 4.4). In the previous answers to the research questions, the level of complexity of this kind of technology has been identified as one of the reasons for the difficulty of grasping the question "what is it?" when trying to identify the properties of the material. Jointly with the complexity of the organisations that currently own these kind of technologies (see 2.1.2).

During the practice, an attempt was made to move from the "what is it?" question to the "what do I need, and why do I need it?" also presented by Manzini as follows: "The boundary now separates those who work with the question, 'What is this?' (for whom specialised and vertical knowledge is still useful) and those who work on the question 'What do I need, and why do I need it?' (for whom new bases in the relationship with the possible must be established) (Manzini, 1989, p. 55). A similar explanation for discarding the first attempt at categorizing and inventorising the data to use a different framework was given during the practice: "I wanted to find a framework that would allow me to think about data in a more abstract and general way, if I wanted to use data as a design tool to solve problems for the users" (section 4.4). The result that was being sought was to "move into an ideation stage when I could further discuss possible design concepts with experts like data scientists or developers". For this reasons, a framework to abstract the concept of "data" was generated — described in sections 4.4, 4.5 and 4.6.

The framework used three types of classifications for "big data": human-sourced information, process-mediates data and machine-generated data. This allowed the design practice to be able to name different data sources at a very high level. While the first attempt at categorising and inventorising the data required a deep knowledge of each data type to even begin to do design work, the latter only required a high level and abstracted awareness of what data was possible to collect/process. In Manzini's words, it focused more on the question "what do I need, and why do I need it?". Considering the second augmented reality design concept presented (see 4.6), the question "what do I need, and why do I need it?", can be answered in this way: "I need to identify each appliance's energy usage, for the customer to see and feel energy consumption". In the design practice (see 4.6), abstracting the material requirements this way gave room for exploring possible ways of collecting or generating that kind of data requirements, without first going into a detailed technological descriptions of what was available. In the particular example of the augmented reality concept, understanding what was needed allowed for a material exploration: "... I began to explore possible options in process-mediated and human-sourced data", since machine-generated data proved insufficient (see 4.6).

While this thesis' solution to the challenges of working with "big data" related technologies might be dependent on the organisational context, brief, designer's skills and technology stack, it does still support the idea that "new bases in the relationship with the possible must be established" in this new technological context. In order words, a certain level of abstraction and codification of knowledge of these technologies would need to be achieved, since their complexity and undefined properties make the question "what is it?" very hard to answer.

6. Discussion

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6.1 Conclusions

This thesis aimed to understand the challenges designers face in a new technological landscape, namely "big data" and its related technologies (data analytics, machine learning, artificial intelligence, etc.). To answer the research questions, a review of the existing literature was presented, together with a research through design project done for the energy company Vattenfall and an analysis of the evidence. The industrial context was an essential area of focus during the study, as the context of the practice is of great importance when working with such technologies in a large organisation.

The findings of this thesis show how the practice of design in this new technological landscape faces multiple challenges. These are the high level of complexity of the technology, lack of education/experience of the designer to work in this context, lack of competence in the organisation, missing frameworks and tools for collaboration between data experts and designers and the elusive properties of these technologies. Furthermore, these technologies present new and different properties not comparable with previously well-studied ones like haptics, Bluetooth, RFID, etc. Making existing frameworks and traditional approaches to exploring new digital materials hard to replicate.

Given that “big data” and its related technologies’ integration into everyday products and services is becoming widespread, these challenges will grow exponentially in the upcoming years. Moreover, the application of these technologies go beyond interaction design and HCI: as see in section 2.2.1, even textile and furniture design are dealing with these technologies already. This thesis’ findings, therefore, support Manzini’s call for the generation of theoretical abstractions that can enable designers to work with increasingly complex and rapidly changing technologies such as those presented in this thesis’ practice.

6.2 Lessons learned and limitations

Looking back at how this thesis was planned and executed, certain things could have been done differently. Firstly, the theoretical framework and review of the literature were done after the practice, once all the data had been collected. What should have been done differently is to have a clear research plan before the practice started. Because there was little time to plan before I joined Vattenfall, this was not possible, making the compilation and analysis of the data burdensome at a later stage.

Regarding the design brief, looking back it is clear that the broad scope proved problematic for the practice. While this was a realistic brief — I have worked with similar briefs after the thesis completion — perhaps a narrower focus on a particular technology could have produced more concise research results. While the industrial context of this thesis provides valuable insights on a real-world scenario, research in a lab-type of setting focusing on one dataset or processing technique would be a better way to compare the material properties of these technologies against others.

Finally, one limitation of this study is the specific nature of the practice. Energy companies are not a typical employer for design practitioners. At the time, one or two designers were working in Vattenfall and none of them was working in the product development department. Most of the design work was outsourced, and therefore there wasn’t a clear structure or guideline for designers to work within the organisation.

6.3 Future research

The literature has made significant progress in recent years to study the problems designers face when working with these new technologies. Especially in the field of UX, research has focused on artificial intelligence and machine learning in particular. While the earlier work concentrated in understanding the problems the design practitioners faced, recent studies are focusing more and more on possible ways of overcoming those hardships.

One possibility for further research is to build more cases in similar contexts with designers that have a certain degree of experience in this particular technological environment. Particularly if the focus is on creating different tools and frameworks to tackle the already identified problems. One suggestion could be to research in industrial contexts where most designers are being employed, for example commercial web and mobile application development.

More importantly, there is also a need to test other research methods to explore the properties of these new technologies. Material-centered interaction design, or other material focused methods that have been successful at exploring technologies like Bluetooth, should study these technologies as well.

7. References

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7.1 Literature

_ Abidin, Shahriman Zainal & Christoforidou, Despina & Liem, André. (2009). Thinking and re-thinking verbal protocol analysis in design research. 10.13140/2.1.2971.0404.

_Bardzell, J., Bardzell, S., & Hansen, L. K. (2015). Immodest Proposals. *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems - CHI 15*. doi:10.1145/2702123.2702400

_ Belenguer, J. S. (2015). *Engineering through Designerly Conversations with the Digital Material: The Approach, the Tools and the Design Space*. Stockholm: KTH Royal Institute of Technology.

_ Bergström, J., Clark, B., Frigo, A., Mazé, R., Redström, J., & Vallgårda, A. (2010). Becoming materials: Material forms and forms of practice. *Digital Creativity*, 21(3), 155-172. doi :10.1080/14626268.2010.502235

_ Booth, W. C., Colomb, G. G., & Williams, J. M. (2008). *The craft of research*. Chicago: University of Chicago Press.

_ Boyd, D., & Crawford, K. (2012). Critical Questions For Big Data. *Information, Communication & Society, 15*(5), 662-679. doi:10.1080/1369118x.2012.678878

_ Breslin, M., & Buchanan, R. (2008). On the Case Study Method of Research and Teaching in *Design. Design Issues, 24*(1), 36-40. doi:10.1162/desi.2008.24.1.36

_ Carmona, K., Finley, E., & Li, M. (2018). The Relationship Between User Experience and Machine Learning. *SSRN Electronic Journal*. doi:10.2139/ssrn.3173932

_ Carroll, J. M., & Kellogg, W. A. (1989). Artifact as Theory-Nexus: Hermeneutics Meets Theory-based Design. *In Proceedings of the Conference on Human Factors in Computing Systems* (pp. 7–14). ACM Press.

_ Carroll, John. (n.d.). Human Computer Interaction - brief intro. Retrieved from https://www.interaction-design.org/literature/book/the-encyclopedia-of-human-computer-interaction-2nd-ed/human-computer-interaction-brief-intro_ Dorst, K. (1995). Analysing design activity: new directions in protocol analysis. *Design Studies,16(*2), 139-142. doi:10.1016/0142-694x(94)00005-x

_ Cooper, A., Reimann, R., Cronin, D., & Noessel, C. (2014). *About Face*. New York: John Wiley & Sons.

_ Dove, G.; Halskov, K.; Forlizzi, J.; and Zimmerman, J. 2017. UX Design Innovation: Challenges for Working with Machine Learning as a Design Material. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems* - CHI '17, 278–288. New York, New York, USA: ACM Press.

_ Gartner. (2011). Press release: October 17th, 2011. Retrieved November 4, 2015.

_ Gartner. (2018). Forecast: The Business Value of Artificial Intelligence, Worldwide, 2017-2025. (2018, March 12). Retrieved from https://www.gartner.com/doc/3868267/forecast-business-value-artificial-intelligence

_ Gaver, W. (2012). What should we expect from research through design? *Proceedings of the 2012 ACM Annual Conference on Human Factors in Computing Systems - CHI 12*. doi:10.1145/2207676.2208538

_ Gemignani, Z., & Gemignani, C. (2014). *Data Fluency: Empowering Your Organization With Effective Data Communication*. Indianapolis: John Wiley & Sons.

_ Giaccardi, E., Speed, C., Wolff, A., Gooch, D. & Kortuem, G. Designing with Data: A Designerly Approach to Data and Data Analytics. *DIS '16 Companion Proceedings of the 2016 ACM Conference Companion Publication on Designing Interactive Systems*.

_ Holmquist, L. E. (2017). Intelligence on tap. *Interactions*, 24(4), 28-33. doi:10.1145/3085571

_ King, R. (2014). *Data-Driven Design: Improving User Experience with A/B Testing*. California: O'Reilly Media.
_ Kitchin, R. (2014). *The data revolution: Big data, open data, data infrastructures & their consequences*. London: SAGE Publications Ltd, 152-166.
_ Kuniavsky, M. (2010). *Smart things: ubiquitous computing user experience design*. Amsterdam: Morgan Kaufmann Publisher.
_ Louridas, P. (1999). Design as bricolage: Anthropology meets design thinking. *Design Studies*, 20(6), 517-535. doi:10.1016/s0142-694x(98)00044-1
_ Louridas, P., & Ebert, C. (2016). Machine Learning. *IEEE Software, 33(5)*, 110-115. doi:10.1109/ms.2016.114
_ Lovejoy, J. (2018, January 25). The UX of AI. *Google Design*. Retrieved from https://design.google/library/ux-ai/
_ Manzini, E., & Cau, P. (1989). *The material of invention*. Cambridge, MA: MIT Press.
_ McKinsey & Company. (2011). Big data: The next frontier for innovation, competition, and productivity. McKinsey Global Institute, (June), 156.
_ McNiff, J. (2002). *Action research: principles and practice*. Milton Park, Abingdon, Oxon: Routledge.
_ Myers, B., Park, S. Y., Nakano, Y., Mueller, G., & Ko, A. (2008). How designers design and program interactive behaviors. *2008 IEEE Symposium on Visual Languages and Human-Centric Computing*.
_ Newman, M. W., & Landay, J. A. (2000). Sitemaps, storyboards, and specifications. *Proceedings of the Conference on Designing Interactive Systems Processes, Practices, Methods, and Techniques* - DIS 00. doi:10.1145/347642.347758
_ Norman, D. A., & Verganti, R. (2014). Incremental and Radical Innovation: Design Research vs. Technology and Meaning Change. *Design Issues*, 30(1), 78-96. doi:10.1162/desi_a_00250
_ Ozenc, F. K., Kim, M., Zimmerman, J., Oney, S., & Myers, B. (2010). How to support designers in getting hold of the immaterial material of software. *Proceedings of the 28th International Conference on Human Factors in Computing Systems* - CHI 10. doi:10.1145/1753326.1753707
_ Preece, J., Sharp, H., & Rogers, Y. (2016). *Interaction design: Beyond human-computer interaction*. Chichester: Wiley.
_ Purgathofer, P., & Baumann, K. (2010). Sketching User Experiences: Getting the Design Right and the Right Design. *Information Design Journal*, 18(1), 88-91. doi:10.1075/idj.18.1.13pur
_ Reeker, L., van Langen, P., & Brazier, F. (2016). [UNPUBLISHED] Lessons Learned from Research through Design: An Empirical Research towards Practical Guidelines for Research through Design.
_ Rose, D. (2014). Enchanted objects: design, human desire, and the Internet of things. New York, NY: Scribner.
_ Rowland, C., Goodman, E., Charlier, M., Light, A., & Lui, A. (2015). *Designing connected products: UX for the consumer Internet of things*. Sebastopol: O'Reilly.
_ Rozendaal, M. C., Ghajargar, M., Pasman, G., & Wiberg, M. (2018). Giving Form to Smart Objects: Exploring Intelligence as an Interaction Design Material. Human–Computer Interaction Series New Directions in Third Wave *Human-Computer Interaction: Volume 1 - Technologies*, 25-42. doi:10.1007/978-3-319-73356-2_3
_ Sarkar, P., & Chakrabarti, A. (2013). A Support for Protocol Analysis for Design Research. *Design Issues, 29*(4), 70-81. doi:10.1162/desi_a_00231
_ Schön, D. (1983). *The reflective practitioner: how professionals think in action*. Basic Books, NewYork

_ Simons, H. (2009). *Case study research in practice*. London: SAGE.
_ Sundström, P., Taylor, A., Grufberg, K., Wirström, N., Belenguer, J. S., & Lundén, M. (2011). Inspirational bits. *Proceedings of the 2011 Annual Conference on Human Factors in Computing Systems* - CHI 11. doi:10.1145/1978942.1979170
_ Swann, C. (2002). Action Research and the Practice of Design. *Design Issues, 18*(1), 49-61. doi:10.1162/074793602527562 87
_ Väänänen-Vainio-Mattila K., Olsson T., Häkkilä J. (2015) Towards Deeper Understanding of User Experience with Ubiquitous Computing Systems: Systematic Literature Review and Design Framework. In: Abascal J., Barbosa S., Fetter M., Gross T., Palanque P., Winckler M. (eds) *Human-Computer Interaction – INTERACT 2015. INTERACT 2015. Lecture Notes in Computer Science, vol 9298*. Springer, Cham
_ Ward, J. S., & Barker, A. (2013). Undefined By Data: A Survey of Big Data Definitions. arXiv.org, 2. Cornell University Library.
_ Wiberg, M. (2014). Methodology for materiality: Interaction design research through a material lens. *Personal and Ubiquitous Computing, 18(3)*, 625-636. doi:10.1007/s00779-013-0686-7
_ Yang, Qian. (2018). Machine Learning as a UX Design Material: How Can We Imagine Beyond Automation, Recommenders, and Reminders?
_ Yang, Q., Banovic, N., & Zimmerman, J. (2018). Mapping Machine Learning Advances from HCI Research to Reveal Starting Places for Design Innovation. *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems - CHI 18*. doi:10.1145/3173574.3173704
_ Yang, Q., Suh, J., Chen, N., & Ramos, G. (2018a). Grounding Interactive Machine Learning Tool Design in How Non-Experts Actually Build Models. *Proceedings of the 2018 on Designing Interactive Systems Conference 2018* - DIS 18. doi:10.1145/3196709.3196729
_ Yang, Q., Scuito, A., Zimmerman, J., Forlizzi, J., & Steinfeld, A. (2018b). Investigating How Experienced UX Designers Effectively Work with Machine Learning. *Proceedings of the 2018 on Designing Interactive Systems Conference 2018 - DIS 18*. doi:10.1145/3196709.3196730
_ Zimmerman, J., Forlizzi, J., & Evenson, S. (2007). Research through design as a method for interaction design research in HCI. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems - CHI 07*. doi:10.1145/1240624.1240704
_ Zimmerman, J., Stolterman, E., & Forlizzi, J. (2010). An analysis and critique of Research through Design. *Proceedings of the 8th ACM Conference on Designing Interactive Systems* - DIS 10. doi:10.1145/1858171.1858228
_ Zimmerman, J., & Forlizzi, J. (2014). Research Through Design in HCI. *Ways of Knowing in HCI*, 167-189. doi:10.1007/978-1-4939-0378-8_8
_ Zoha, A., Gluhak, A., Imran, M., & Rajasegarar, S. (2012). Non-Intrusive Load Monitoring Approaches for Disaggregated Energy Sensing: A Survey. *Sensors, 12*(12), 16838-16866. doi:10.3390/s121216838

7.2 Online

_ A 'Brief' History of Neural Nets and Deep Learning. (2015, December). Retrieved August 4, 2018, from http://www.andreykurenkov.com/writing/ai/a-brief-history-of-neural-nets-and-deep-learning/
_ Classification of Types of Big Data - Big Data - UNECE Statistics Wikis. (n.d.). Retrieved from https://statswiki.unece.org/display/bigdata/Classification of Types of Big Data
_ Data hub. (2018). Retrieved from https://www.svk.se/en/stakeholder-portal/Electricity-market/data-hub/

_ HIARCS Palm Chess Ratings. (n.d.). Retrieved from http://www.hiarcs.com/phresults.htm
_ Large Scale Visual Recognition Challenge 2012 (ILSVRC2012). (n.d.). Retrieved from http://image-net.org/challenges/LSVRC/2012/results.html
_ Large Scale Visual Recognition Challenge 2010 (ILSVRC2010). (n.d.). Retrieved from http://image-net.org/challenges/LSVRC/2010/index
_ Parloff, R. (2016). Why Deep Learning Is Suddenly Changing Your Life. Retrieved September 10, 2018, from http://fortune.com/ai-artificial-intelligence-deep-machine-learning/
_ User-Centered Design Basics. (2017, April 03). Retrieved from https://www.usability.gov/what-and-why/user-centered-design.html

7.3 Design practice data

_ Customer data records. (2015). Vattenfall.
_ Framework brainstorm. (n.d.) Gaspar Mostafá.
_ Data Scientist A. (2015, October 21). Personal interview.
_ Data Scientist A. (2015, November 19). Personal interview.
_ Data Scientist B. (2015, October 21). Personal interview.
_ Design notes. (2015, July 6). Gaspar Mostafá.
_ Design process notes. (2016, January 15). Gaspar Mostafá. Compiled after the final presentation.
_ Energy expert and data scientist. (2015, July 30). Personal interview.
_ Energy expert. (2016, January 1). E-mail communication.
_ Final report. (2016, February 2). Gaspar Mostafá.
_ Final presentation feedback. (2016, January 19). Personal communication.
_ Internal report A. (2015, October 5). Access through Vattenfall computers only.
_ Internal report on personas. (2015, June 1). Access through Vattenfall computers only.
_ Mid-term presentation feedback. (2015, n.d.). Personal communication.
_ Product developer A. (2015, July 19). Personal interview.
_ Reading list. (2015, March 29). Gaspar Mostafá.
_ Supervisor. (2015, June 15). E-mail communication.
_ Supervisor. (2015, July 7). E-mail communication.
_ Supervisor. (2015, October 22). E-mail communication.
_ Stakeholder meeting. (2015, May 14). Personal meeting.
_ Vendor meeting. (2015, July 1). Personal meeting together with stakeholder.
_ Vendor meeting notes. (2015, July 1). Gaspar Mostafá.

Figures, tables and illustrations created by the author unless mentioned otherwise.

8. Appendix

A: A definition of “big data”
B: Practice related literature during the design practice
C: Augmented reality concept sketches

Apppendix A: A definition of “big data”

There’s no single industry definition of the term, but Kitchin lists the following characteristics:

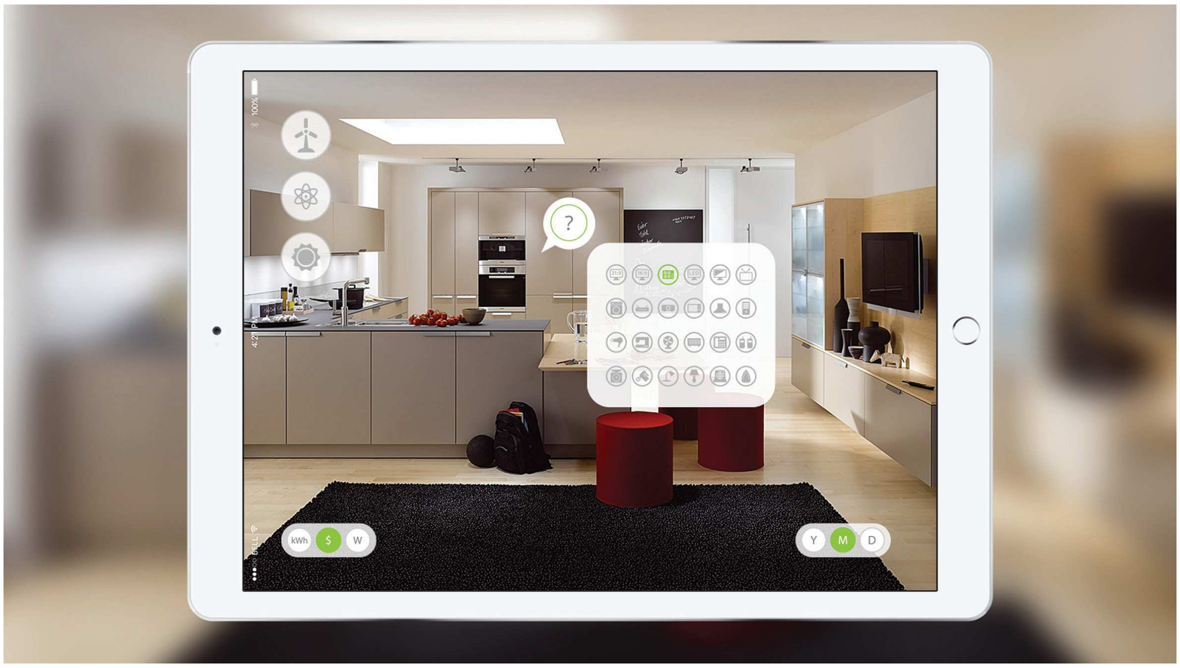
• Huge in volume, consisting of terabytes or petabytes of data;
• High in velocity, being created in or near real-time;
• Diverse in variety, often temporally and spatially referenced;
• Exhaustive in scope, striving to capture entire populations or systems, or at least much larger sample sizes than would be collected in traditional, small data studies;
• Fine-grained in resolution, aiming to be as detailed as possible;
• Relational, containing common fields that enable the conjoining of different data sets;
• Flexible in extensibility (can add new fields easily) and scalability (can expand in size rapidly) (Kitchin, 2013, p. 3).

Apppendix B: Practice related literature during the design project

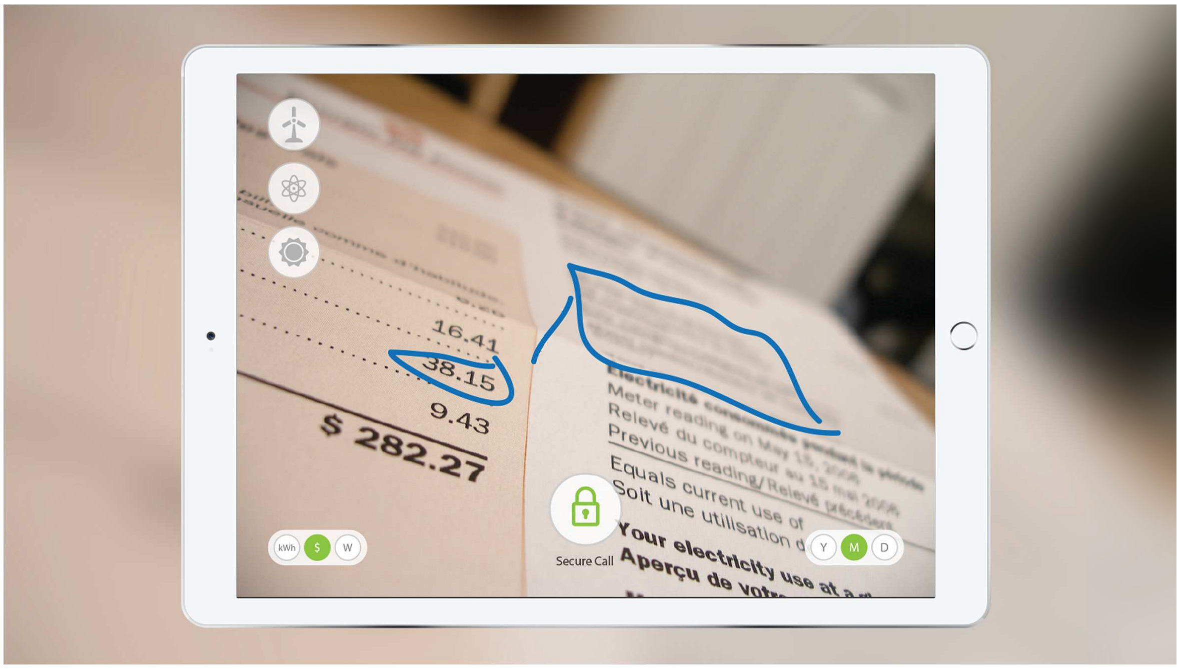
29.03.15, Learning to see data
31.03.15, Telling your data's story
01.04.15, Augmenting human intellect, a conceptual framework
02.04.15 Data versus insights
02.04.15 The origins of data visualization
02.04.15 How Helsinki became the most successful open-data city in the world
03.04.15 How the Nest learning thermostat works
07.04.15 Fifteen timeless data science articles
10.04.15 Get ready for hybrid thinking
12.04.15 How far can machines go understanding content?
13.04.15 The real reason open source startups fail
13.04.15 Welcome to NASA's data portal
16.04.15 What data won't tell you
23.04.15 Highest voted questions, stackexchange
23.04.15 How data visualization is transforming the construction industry
25.04.15 Users' views on the potential impacts of open data and open government
29.04.15 BigML is machine learning for everyone
30.04.15 Big-data-as-a-service
30.04.15 20 bullets on artificial intelligence
05.05.15 Why your brain loves infographics
05.05.15 Good visualisations can change the conversation
05.05.15 How not to drown in numbers
06.05.15 Big data is dead, long live big data
08.05.15 Ten NLP terms
08.05.15 The secret to creativity, intelligence and scientific thinking
10.05.15 Human information interaction, MIT press
10.05.15 Human information retrieval, MIT press
12.05.15 Visualization in R
12.05.15 How artificial intelligence and big data will transform the workplace
13.05.15 Thinking like a data scientist
14.05.15 Seven ways to gain value from data scientists
16.05.15 Data visualization & Kant's work
16.05.15 How data can inspire creativity
16.05.15 Understanding brains: details, intuition and big data
16.05.15 The extended mind
18.05.15 What big data means for psychological science
03.06.15 NAB, a benchmark for streaming anomaly detection
07.06.15 If you really want to save energy at home, forget about the light switch
07.06.15 The online privacy lie is unravelling
07.06.15 A city view of the sharing economy
07.06.15 Apple introduces HomeKit
08.06.15 First connected home devices for Apple's HomeKit
08.06.15 Japanese smart homes
11.06.15 To handle big data, shrink it
14.06.15 The library of the future must be digital + physical
17.06.15 U.S. tech funding
23.06.15 Exploring the 7 different types of data stories
25.06.15 Open data thanks to value on creativity
05.07.15 Information visualisation, human-computer interaction and visual analytics
07.07.15 Difference between machine learning and statistical modelling
10.07.15 The internet of no-things
22.07.15 Transforming the miCoach experience into a smartwatch
23.07.15 Rise of collaborative commons
05.08.15 Designing data for good initiatives
15.08.15 Understanding the 'shape' of data
23.07.15 Google introduces project sunroof
31.08.15 U.S. residential solar financing 2015-2020
23.09.15 Scientific American infographics
25.09.15 Data scientist and storytelling
10.10.15 Intelligence amplification
24.10.15 Big data, analytics and the path from insights to value
26.10.15 Data science machine
30.10.15 A very short history of data science
04.11.15 The current state of machine learning
04.11.15 The current state of machine intelligence
08.11.15 Ten aspects of highly effective research data
11.11.15 Deep learning: intelligence from Big Data
16.11.15 Google: machine intelligence and human intelligence
21.11.15 Thinking like a designer in machine learning
21.11.15 Image recognition and deep learning

Appendix C: Augmented reality concept sketches

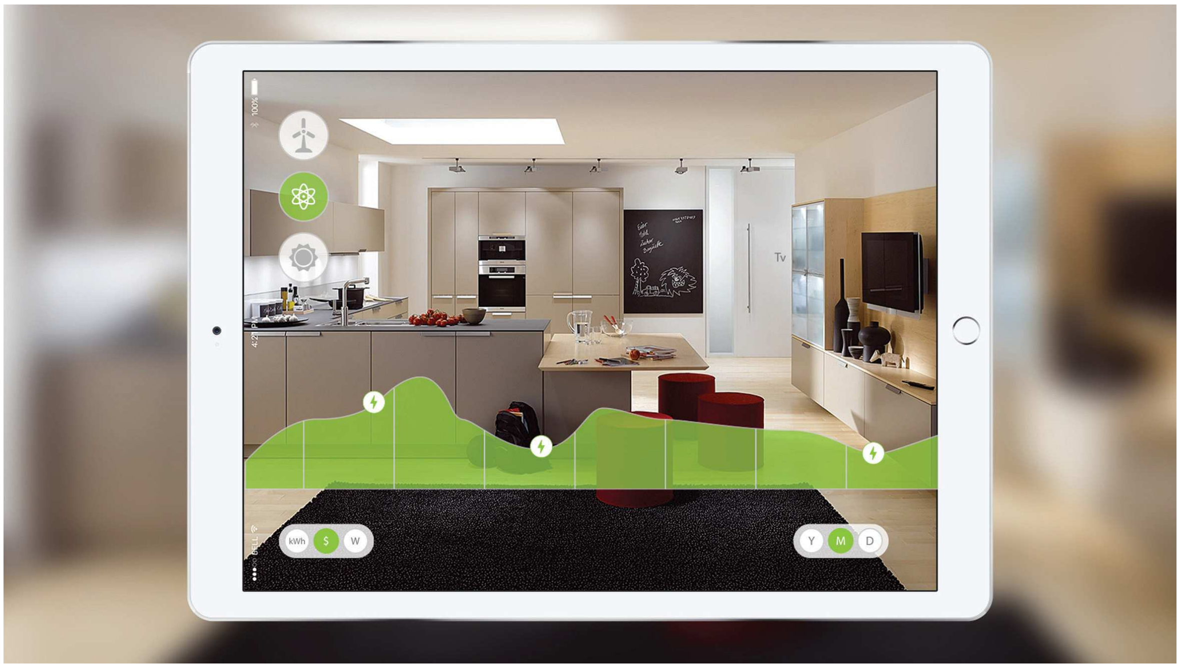
Augmented reality sketch: user input alternative method.



Augmented reality sketch: user input alternative method.



Augmented reality sketch: secondary uses (invoice communication interaction)



Augmented reality sketch: daily appliance consumption graph.