Data Science for Service Design

An exploration of the opportunities, challenges and methods for data mining to support the service design process

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Data Science for Service Design: An exploration of methods

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This research identifies the opportunities for data science to support the service design process through exploration of data science methods for service designers. Designers and their teams search for a data techniques overview from their perspective as designers, while current literature is fragmented and technical. This research explores methods to help them get started. It evaluates if the techniques meet the designer's needs and fit the design process with user-centred activities, such as shadowing sessions and workshops. As a result, this thesis contribute to the diversity of the designers' methodology toolkit. They increase the validity of user research, make hidden information accessible with specialised user research tools and help designers in their creative process through relevant resources, inspiration and an alternative perspective. Together these results encourage organisations to mature with data science resources for design projects so that their services benefit from more informed designers.

Keywords: Service Design, Concept Design, Data Mining, Data Science, Process Mining, Data-driven Design, Mixed Methods.

Contents

Reader's guide

The reader's guide is a reference to the chapters of this thesis. Readers interested in the research process may follow the research path of chapters 1, 4, 7 and 8. Other readers might look for global (Chapter 5) and specific ways (Chapter 6) to combine data science and design. Background chapters in Service Design (Chapter 2) and Data Mining (Chapter 3) might be relevant before diving into the details. In that case, path 1, 2, 3, 5, 6, and 7 is recommended.

II

4. Research process

This explorative study researches how data mining supports service design by creating concepts of data science methods for service designers. User-centred and creative activities play an important part in the process.

I

1. Introduction

The increase in user data creates data mining opportunities for service designers, which this research examines and maps.

2. Service Design

Service Design is enabling the service provider and users to co-create value, by means of holistic view and user-centred methods.

3. Data Mining

Data Mining is the process of automatically identifying meaningful information or useful patterns from big data.

X

Y. Legend

Summary of Chapter Y, named Legend, of part X. Continue with Chapter Z.

Z. Example chapter

Summary of the second chapter of part X: Example chapter Z. The chapter follows Chapter Y.

III

5. Design and Data mining

This chapter answers where the opportunities lay for both service design and data mining, how organisations mature in this field, and what the challenges are when we collaborate.

6. Data mining methods for service designers

This research identified concepts for data science methods in the service design process. They are presented in four categories.

User research
Data mining makes insights available with specialised user research tools.

Systems
Data science analyses complex systems such as customer journey mapping.

Serendipity
Inspiring and insightful generated materials are useful for serendipity.

Collaboration
Mixed teams join forces to collaborate more effectively.

IV

7. Discussion

In the discussion, the findings and research implications for practitioners and academic service designers are discussed.

8. Conclusion

The conclusion closes with answering the research questions, limitations and future work for using data science in the service design process.

Part I

Introduction

Chapter 1

Introduction

Services are an undeniable force behind value creation (Secomandi & Snelders, 2011), and service innovation is crucial to economic and social development (Patrício, Gustafsson, & Fisk, 2018). Several influences, such as the increasing consumer demands and complexity of technology, require that service providers improve their services (Spiess, T'Joens, Dragnea, Spencer, & Philippart, 2014).

Service design is the design discipline that designs for services; enabling the value co-creation between the service provider and user (Costa, Patrício, & Morelli, 2018; Patrício et al., 2018; Kimbell, 2011). The increase in service demand and technological complexity puts pressure on the service designers. Academia and industry call for a need for interdisciplinary methods (Patrício, Fisk, Falcão e Cunha, & Constantine, 2011).

Data science and data mining offer opportunities for designers, because their goal is to extract meaningful knowledge from data (van der Aalst, 2014a) and the amount of data from or about the users grows, e.g. consumer-generated content (Xiang, Schwartz, Gerdes Jr, & Uysal, 2015).

As a result, many initiatives apply data mining, for instance, in marketing (Murray, Agard, & Barajas, 2018; Tan, Steinbach, & Kumar, 2006), product design (Köksal, Batmaz, & Testik, 2011; Köksal et al., 2011) and ethnography (Weibel et al., 2013). Data science techniques also proved useful for projects closer to service designers, such as, among others, mapping the customer experience (Bernard & Andritsos, 2017a), and understanding social and economic behaviour (Xiang et al., 2015).

Although these studies provide useful insights, literature is fragmented over multiple areas such as process mining and natural language processing. Furthermore, to our knowledge, they offer no validation with service designers or explicitly address their needs.

Many design agencies, such as Mirabeau, service designers and their teams look for ways for utilising these data mining techniques from their perspective as designers. They acknowledge the potential, but miss familiarity to form a complete picture of the possibilities, risks and best matches with their projects. This research aims to provide key information in an overview of when and how data mining is useful to support the service design process. The explorative, qualitative research process resulted in a guide to data science methods for service designers.

1.1. Research focus

This research brings service design and data mining together to explore the possibilities for combining these fields and answers the following research question:

When and how can Data Mining be used to support Service Designers?

The objective of this research is to help service designers and their organisations so that they can orient and select data mining techniques for their design projects. It is essential that the research meets the needs of the designer and fits the design process. Furthermore, it should address the feasibility of the data mining techniques. Therefore, this research will 1) examine desirability from the perspective of the designer (both academic and practise), and 2) include a technical foundation for the data mining methods.

This study conducts explorative and qualitative research with both academic and practical designers in user-centred activities throughout the process. Designers from the company Mirabeau were participants in workshops, such as interviews, shadowing sessions and other. Mirabeau is a digital agency with clients in multiple fields, such as B2B, finance, retail and travel (Mirabeau, n.d.), and practises service design.

Secondly, this research addresses the technical feasibility and extends the scope of data mining to data science. Data mining and data science are not equal; nevertheless, this study includes other data science techniques, such as process mining, next to data mining. The techniques are related and mainly differ in the data sources. Their main goal is to extract meaningful knowledge from data (van der Aalst, 2014a). A strict distinction formed on the definitions will rule out (parts of) concepts unnecessarily.

1.2. Research procedure

This study researched how data mining can support service designers by developing a guide to concepts of data science methods in an iterative research process. In the development, both academic and practical designers were involved with user-centred activities. We can distinguish the following main phases in this research process: exploration, ideation and evaluation.

The first phase of the research, **exploration**, focused on defining the research areas, understanding designers and data scientists and create a mental framework. Shadowing, interviewing, and literature review were the essential activities in this phase. The exploration phase centred the following subquestions:

1. What does the Service Design process need?
2. What can Data Mining offer?

These opportunities grew and were pruned in the **ideation** phase, resulting in the guide to data science and team methods. Refining the ideas included designer participation, case studies and speculative cases. The main activities in this phase consist of brainstorm methods, paper tools and feedback sessions with designers.

The **evaluation** phase aimed to test the usability and desirability of the methods, reflection and conclude overall findings from this research. Workshop sessions with designers, self-reflection, discussions and a panel interview substantiated this phase.

1.3. Outline of the thesis

First, the thesis discusses Service Design and Data Mining in more detail.

Chapter 2
Service Design

Chapter 2 starts with the definition of Service Design (Section 2.1). In the *Service Design process* section (Section 2.2.1), a new design process model is proposed: the holistic double diamond. This model separates diverging and converging activities and includes a broader timeline for clear matches with the data science methods. The chapter also discusses the way of working at Mirabeau and their service designers (Section 2.2.2). The most prominent Service Design methods (Section 2.2.3) close this chapter.

Chapter 3
Data Mining

Data Mining chapter (Chapter 3) discusses the terminology of Data Mining and Data Science (Section 3.1), the processes involved (Section 3.2) and some leading techniques (Section 3.2.2).

Chapter 4
Research process

The fourth chapter, called *Research process*, explains the methodology of this research and expands on the three phases: exploration, ideation and evaluation. It discusses, among other things, the shadowing sessions, creation of 'method cards', evaluation workshops and the final selection.

Chapter 5
Design and Data mining

The general strengths and opportunities for Design and Data mining continue in Chapter 5. For example, Section 5.1 discusses the importance and data science contributions of method triangulation. A variation on a maturity model is proposed to map the challenges that organisations might face when implementing data mining (Section 5.2).

Chapter 6
Data mining methods for service designers

The next chapter, *Data mining methods for service designers*, presents the methods in detail. The overview (Section 6.1) discusses how the methods relate to each other, the required data science capabilities and the service design process. The quick start guide (Section 6.1.3) points to specific methods to help the design team get started. Furthermore, a hypothetical case is introduced that illustrates applied examples of the methods (Section 6.2).

Four categories introduce the eleven methods: 1) user research tools, 2) analysing complex systems such as customer journey mapping with process mining, 3) inspiring and insightful generated materials for serendipity and 4) joining forces with data scientists in mixed teams.

1. User research (Section 6.3)
   Data mining can make hidden information accessible to designers with specialised user research tools, and therefore designers can measure more factors of users. The category contains two methods. *Opinion mining* (Section

6.3.1) analyses large amounts of user-generated text, such as customer feedback, while *Bio translations* (Section 6.3.2) focus on unravelling user emotion and behaviour.

2. Systems (Section 6.4)
   Process mining can support designers with understanding and testing models of systems, such as mapping the actual and expected *Customer journey* (Section 6.4.1).

3. Serendipity (Section 6.5)
   Data mining can help designers in their creative process through relevant resources, inspiration and an alternative perspective. The first two methods of this category will focus on the materials involved in the design projects by scouting these materials in *Explore Tools, Artifacts and Insights* (Section 6.5.1) or analysing them in *Meta analyse* (Section 6.5.2). The other two methods stimulate inspiration and insights with *Generating artifacts* (Section 6.5.3), such as personas, and defying predefined structures in *Segmentation* (Section 6.5.4).

4. Collaboration (Section 6.6)
   The design team can collaborate more effectively with the data scientists and analysists. This category contains four small methods that are not based on specific data science techniques.

The thesis concludes this research in the last chapters: *discussion* and *conclusion*.

Chapter 7 Discussion

Chapter 7 discusses the findings of this research and its implications. The examined method groups, opportunities and challenges provide insight into the ways that data science can support the design process. Design teams should check how they can integrating data mining and design projects to upgrade their user research and creative design process.

Chapter 8 Conclusion

The *conclusion* (Chapter 8) answers the research question (Section 8.1). Furthermore, the chapter discusses the research limitations (Section 8.2) and suggests future work (Section 8.3).

Chapter 2

Service Design

Service Design is "is a process that brings together skills, methods, and tools for intentionally creating and integrating ... systems for interaction with customers to create value for the customer, and, by differentiating providers, to create long-term relationships between providers and customers" (Evenson & Dubberly, 2010, p. 2). This chapter describes the *Definition of Service Design* (Section 2.1) in detail and ends with *Service Design in practice* (Section 2.2) that reviews the service design process, common design methods and way of working at company Mirabeau.

2.1. Definition of Service Design

Although service design relates to other fields in design, service design offers a unique perspective. It is the design discipline, which concerns not solely about a single product or service, but the value co-creation between the service provider and user (Costa et al., 2018; Patrício et al., 2018; Forlizzi & Zimmerman, 2013). Therefore, service designers model the holistic experience and inclusive environment of services (Yu & Sangiorgi, 2014; Zomerdijk & Voss, 2010). This environment contains social, material, relational elements (Zomerdijk & Voss, 2010; Kimbell, 2011). Service designers work typically with user-centred methods, where users and all stakeholders are involved as much as possible (Evenson & Dubberly, 2010; Stickdorn, Schneider, Andrews, & Lawrence, 2011).

During the literature review, the following characteristics of service design reoccured: holistic, user-centred, and value-creation (Figure 2.1). Therefore, I propose the following definition of service design:

Service Design is

1. enabling the service provider and users to *co-create value*,
2. by means of *holistic* view and *user-centred* methods.

Authors (year)	Title	Value	Holis	User
Zomerdijk and Voss (2010)	Service design for experience-centric services.	✓	✓	✓
Patrício et al. (2018)	Upframing service design and innovation for research impact.	✓	✓	✓
Forlizzi and Zimmerman (2013)	Promoting service design as a core practice in interaction design.	✓	✓	✓
Evenson and Dubberly (2010)	Designing for service: Creating an experience advantage.	✓		✓
Kimbell (2011)	Designing for service as one way of designing services.	✓	✓	✓
Stickdorn et al. (2011)	This is service design thinking: Basics, tools, cases.	✓	✓	✓
Yu and Sangiorgi (2014)	Service design as an approach to new service development: reflections and futures studies.	✓	✓	✓

Value	Holis	User
Value (co-)creation	Holistic experience	User-, customer- or human-centred

Figure 2.1. Overview of the characteristics of service design in literature.

Co-creation of value

The first characteristic of service design is the co-creation of value between the service provider and users (Evenson & Dubberly, 2010; Sangiorgi, 2012). Service design is not 'a discipline about designing services', but 'designing for service' (Kimbell, 2011) because designers create opportunities where actions and interaction can support the co-creation of value and meaning (Yu & Sangiorgi, 2018; Evenson & Dubberly, 2010; Kimbell, 2011). The service provider produces the resources and processes for value propositions that the users integrate with their resources (Yu & Sangiorgi, 2018).

The experience (value-in-use) and service are intangible (Zomerdijk & Voss, 2010; Secomandi & Snelders, 2011; Yu & Sangiorgi, 2018) and tangible and intangible resources form the basis of value-creation (Patrício et al., 2018). Yet, the service is created by designing the tangible: interface, sociotechnical resources, artifacts, service evidence (Secomandi & Snelders, 2011).

Holistic

The holistic approach is the second characteristic of service design (e.g. Yu & Sangiorgi, 2014; Zomerdijk & Voss, 2010; Forlizzi & Zimmerman, 2013). In service design, designers have 1) holistic view on the experience of the user (e.g. Costa et al., 2018; Patrício et al., 2018), along with 2) a holistic approach to structures, infrastructure and processes of a service (Goldstein, Johnston, Duffy, & Rao, 2002; Yu & Sangiorgi, 2014). Appendix A2 describes the full review of the holistic experience and integrative approach of service design.

A benefit of a looking at the bigger picture is preventing so-called short-sighted design bias (Garde, 2013). This bias leads to a local maximum of experience instead of the global maximum. Complex systems especially require a holistic view to preventing local maxima. Service design provides a system thinking needed for complex cases such as societal concerns (Forlizzi & Zimmerman, 2013).

Service designers view the customer experience as holistic, which follows the journey over time, across mediums, beyond touchpoints and with all senses. The holistic experience is:

Temporal	(Halvorsrud, Kvale, & Følstad, 2016; Yu & Sangiorgi, 2014; Forlizzi & Zimmerman, 2013)
Multi-sensory	(Pullman & Gross, 2004; Stickdorn et al., 2011; Zomerdijk & Voss, 2010)
Emotional	(Yu & Sangiorgi, 2014; Zomerdijk & Voss, 2010)
Intangible	(Zomerdijk & Voss, 2010; Secomandi & Snelders, 2011; Patrício et al., 2018)
Tangible	(Kimbell, 2011; Stickdorn et al., 2011; Secomandi & Snelders, 2011)
Cross-channel	(Sousa & Voss, 2006; Osterwalder, 2004; Rayport & Jaworski, 2004)
Relational and social	(Zomerdijk & Voss, 2010; Forlizzi & Zimmerman, 2013; Yu & Sangiorgi, 2014)

The analysis of the service provider and its relations holds the key to the service as well. Service design concerns the integrative view of infrastructure (employees, customers, stakeholders and designers), structures (physical, technical and environmental), organisation (front- and backstage, Figure 2.2) and processes of a service (activities to deliver service):

Infrastructure	(Secomandi & Snelders, 2011; Yu & Sangiorgi, 2014; Goldstein et al., 2002)
Stakeholders	(Forlizzi & Zimmerman, 2013; Costa et al., 2018; Yu & Sangiorgi, 2014)
Organisation	(Patrício et al., 2018; Kimbell, 2011; Sangiorgi, 2010)
Structure	(Goldstein et al., 2002; Yu & Sangiorgi, 2014; Secomandi & Snelders, 2011)
Processes	(Kimbell, 2011; Zomerdijk & Voss, 2010)

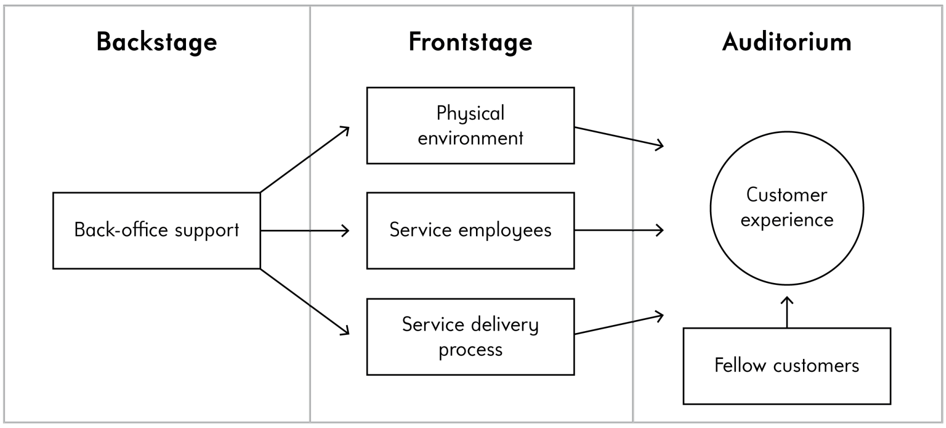


Figure 2.2. The drama metaphor displays three organisational areas of a service; backstage, frontstage and auditorium (Zomerdijk & Voss, 2010).

User-centred

The user-centred approach is the third characteristic of service design because the interaction between the actors is what creates the service (Secomandi & Snelders, 2011; Stickdorn et al., 2011; Yu & Sangiorgi, 2014). Literature calls service design also stakeholder-centred (Forlizzi & Zimmerman, 2013), experience-based (Kimbell, 2011), customer-centred (Halvorsrud et al., 2016) or human-centred.

A user-centred approach creates services that are personal and memorable (Zomerdijk & Voss, 2010), along with meaningful, compelling and fulfilling (Evenson & Dubberly, 2010). The experiences address the users needs and wishes (Evenson & Dubberly, 2010) because designers understand the service delivery process from a customer's perspective (Halvorsrud et al., 2016). Translating needs of the users results in more effective services (Patrício et al., 2018) and user-centred services support long term relation customer relations (Evenson & Dubberly, 2010).

The holistic and experience-centred approach is multi-sensory, emotional and relational. Examples of holistic and user-centred models are the prominent customer journey and service blueprint, which provide overviews of the experience and service from the point of the user and stakeholders. The service design process contains many user-centred methods to understand and deliver to the user, which *Service Design in practice* (Section 2.2) discusses.

2.2. Service Design in practice

This section discusses the practical side of service design. In the *Service Design process* (Section 2.2.1), I propose a new design process model based on the shortcomings of the current model noticed in this research. Next, Section 2.2.2 describes the way of working at the company Mirabeau. The chapter ends with an overview of the prominent *Service Design methods* (Section 2.2.3).

2.2.1. Service Design process

The design process is a non-linear iterative process of diverging and converging. Although it is circular, different phases can be represented in an outline structure (Stickdorn et al., 2011). The structure is not strictly followed because an iteration in one of the phases could contain parts of other phases or redirect to an earlier phase. Most service designers base their process on the double diamond model (Yu, 2017). The double diamond stands for two sets diverging and converging phases: Discover & Define and Develop & Deliver (Figure 2.3a). In this thesis, I propose a new variation called the 'holistic double diamond' (Figure 2.3c).

The holistic double diamond

In this research, an adaption of the double diamond (DD) is introduced to represent the service design process: the holistic double diamond (HDD). The HDD contains two similar diverging and converging diamonds but has a broader view to include the designer's activities and involvement outside the scope of the DD and similar models (Figure 2.3). Yu (2017) also stated that the service implementation are unknown or limited in these service design processes models.

The new outer phases are Prepare and Maintain. Prepare is the phase that involves the activities of the service designer before kickstarting the project, such as preparing the service design process and perhaps explaining what service design is to the client (Stickdorn et al., 2011). The end phase is Maintain, where designers continue in assisting the services without starting a new project.

The second difference is placing Implement out of the diamond and making room for an explicit Test phase. Some models include the Test in Ideate (Yu, 2017), but in other cases, evaluation is treated as a separate phase[1] (Stickdorn et al., 2011). This research uses a model that makes testing explicit to demonstrate the different needs and possibilities for designers. Additionally, ideation is a diverging process, while testing is not. Testing is converging, and the DD does not address this contrast.

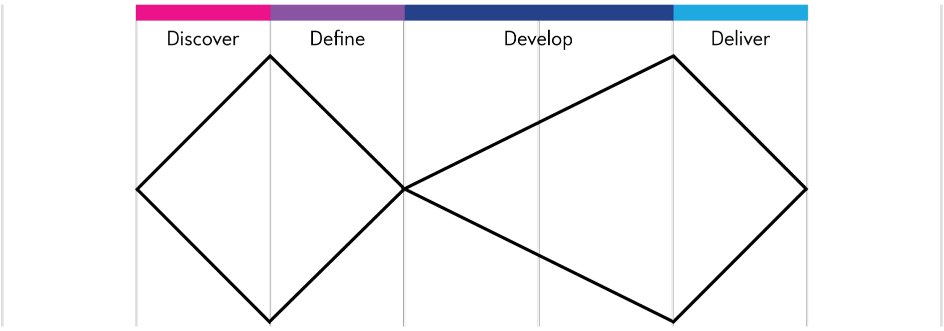
The diamonds represent iterative matches between two circular diverging and converging activities, such as the first diamond (Understand & Define[2]) is for the problem space. Ideate and Test are a similar match in the solution space. However, the original DD made Implement the counterpart of Ideate. In practice,

[1] Stickdorn et al. called it Reflection.

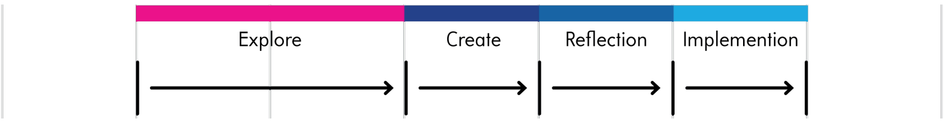
[2] In original double diamond called Discover & Define.

is implementation after thé solution is selected and therefore after the converging phase.

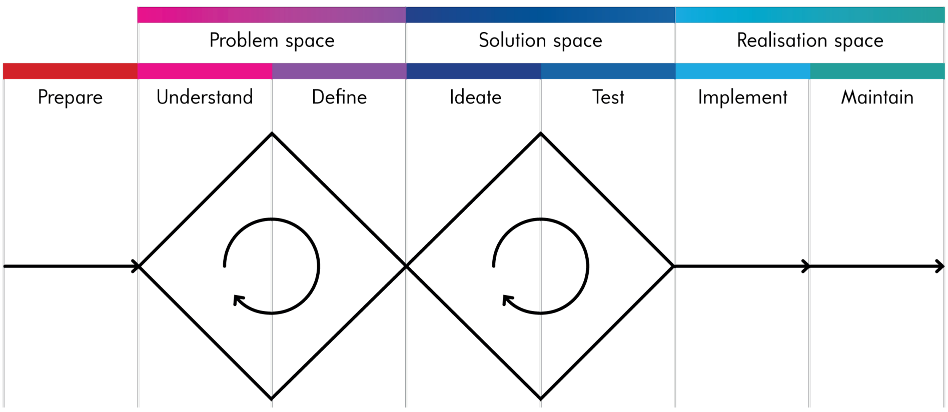
Therefore, the Implement phase is not part of the HDD solution space diamond because it does not directly follow the diverging end of Ideate. Test is a valid and converging phase that does belong in the solution space as the iterative match with Ideate.



(a) The double diamond (Stickdorn et al., 2011; Yu, 2017).



(b) The service design process by Stickdorn et al. (2011).



(c) The HDD: holistic double diamond.

Figure 2.3. Comparison of the stages in the three service design process models.

The labels in HDD are slightly different as well. Figure 2.3 shows how the labels of the different models relate to each other (e.g. Deliver, Implementation and Implement). The phases of HDD are:

Prepare Before kickstarting the project is decided that and in which direction the project takes place. The main goal of this phase is preparing for the process and project, e.g. with pitches and stakeholder convincing.

Understand In this diverging phase, the designer explores the problem space for the true problem and creates a holistic view to understand the complicated situation (Stickdorn et al., 2011). This phase contains a great deal of design and user research.

User research

Methodology for understanding the behaviors, needs and motivations of users (and stakeholders). Sometimes called design research.

Define Findings from the analysis are summarised and concluded in the creative brief, that defines the identified possibilities, underlying structure and design challenge (Yu, 2017; Stickdorn et al., 2011).

Ideate Concepts are developed in the ideate phase with an iterative process (Stickdorn et al., 2011) for creating and refining solutions (Yu, 2017).

Test Iterative designing is “process of trial and error” (Yu, 2017, p. 30), and testing is essential to evaluate the trials with prototyping, user tests and reflection.

Implement The service concept is realised and launched, where the involvement of employees management is crucial (Stickdorn et al., 2011).

Maintain After implementing the service concept, design activities take place to continue and improve the service. In this phase, the service is measured to learn and increment before starting a new project.

2.2.2. Design at Mirabeau

Mirabeau is a digital agency with clients in multiple fields, such as B2B, finance, retail and travel (Mirabeau, n.d.). They aim to create digital solutions centred around customer needs and behaviour with design, technology and insights (Versteeg, 2019).

The designers from Mirabeau were involved in this research during various phases, what will be explained in the *Research process* (Chapter 4). Insights about how Mirabeau applies design results from interviews, shadow sessions and workshops. In total, nine interaction designers, two creative consultants and a visual designer participated. Alphabetic letters represent the participants for privacy reasons.

Design process at Mirabeau

The design process of Mirabeau is divided into the five phases where design, insights and development collaborate (Figure 2.4) (Versteeg, 2019). The whole process and each phase are agile, represented by the growth cycle, also called the growth loop. The phases are described as following (Versteeg, 2019, p. 30):

Define Align on the goal of the project and setting the stage for a successful collaboration.

Understand A mixed team of specialists works to understand the context of the challenge through research.

Concept Based on the understanding, ideas are iterated to achieve the experience that is needed.

Produce The concept is now being crafted. In a mixed team, the product is designed, developed and tested towards a fully working product.

Measure The product is aligned with the KPIs, and new goals to improve are defined.

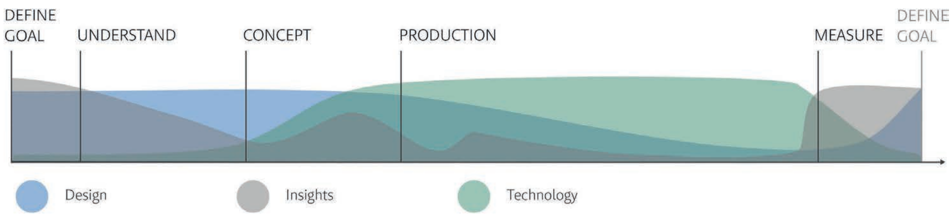


Figure 2.4. The 'way we work' of Mirabeau (Versteeg, 2018).

The SCRUM framework structures most projects and most designers are explicitly part of the development team. SCRUM is an agile framework for software development with time-boxed iterations called sprints and time-boxed meetings.

User story

Description of feature(s) and requirements of a system from point of a user.

Many designers work in the sprint rhythm, and the designers' deliverables are included in the sprint (e.g. user stories). Their work covers both concept and interaction design, and the designers work closely with some other disciplines such as visual design (sharing and working on designs) and front-end development (brainstorming about requirements).

Digital service designers at Mirabeau

Mirabeau distinguishes no different roles for service and interaction design. None of the interaction designers has separated role as strategic, service, concept or interaction designer. One of the designers, Designer B, believes that all interaction designers at Mirabeau are essentially both concept and interaction designers. The design process of a project makes a continuous flow, where it is hard to point at service or interaction. The designer states that project and personal features determine the balance between the two specialities. For example, the background and/or experience of a designer makes it more natural to use the holistic view of service design.

In our interview, Designer B states that service design at Mirabeau can, in essence, never be as holistic as the pure service design discipline requires. As a digital agency, Mirabeau has a digital lens. The solution will always involve a digital system and the designers have a digital bias. For example, live|work developed a (non-digital) staff training as a final product, where Mirabeau would develop something digital. The designer would instead call the concept designers at Mirabeau "digital service designers".

Some projects have an almost exclusively interaction design role. For example, Designer E continues from a pre-defined concept, design principles and roadmap. The new designs include only visual and interaction design and have no focus on the concept or service (anymore). In contrast, other designers show all characteristics of service design in their projects: holistic view, user-centred methods and value creation.

The holistic approach is demonstrated in Designer J's project, which included more than the small scope of the development team or end-users. The organisation has changed much because of the design process. Initially, the design team was "used" as a part of the production, tells the visual designer. The stakeholders were not aligned, and the other departments not engaged. In order to understand and improve the service of the organisation, Designer J aligned a large number of stakeholders and gained insight into the organisation itself. Together the designers had a strategic role and engaged all departments of the organisation with design thinking, weekly "hands-on" meetings and "crazy about user experience" meetings.

Both the concept designers and interaction designers at Mirabeau practise user-centred methods such as interviews and user testing. Additionally, the processes performed by users and systems are mapped in service artifacts and deliverables - the designers present these customer journeys and service blueprints proudly on the walls.

2.2.3. Service Design methods

This section will provide a small overview of design (thinking) methods used by service designers. Many other design methods exist and are practised daily by service designers next to this small collection.

Stickdorn et al. (2011) collected everyday practised tools and methods by crowdsourcing the service designers community. The following methods from their toolbox (Stickdorn et al., 2011) occur in the *Research process* (Chapter 4) or *Data mining methods for service designers* (Chapter 6):

(Contextual) interviews

With interviews, the users or other stakeholders are questioned in a structured, semi-structured or unstructured way, and interviewing in their environment aids in more details and 'lively' stories (Stickdorn et al., 2011).

Customer journey map

The customer journey is a metaphor for the timeline of a service in perspective of the customer (Halvorsrud et al., 2016) and contains the moments of service interactions called touchpoints (Stickdorn et al., 2011). The mapping method is capturing this journey in a schematic and visual overview: the customer journey map (Figure 2.5). Customer journey mapping can reveal problems and opportunities, and the map can be used for communication (Stickdorn et al., 2011).

The touchpoint of a customer journey contains the interaction of the customer with other humans, machines or even machine to machine (Stickdorn et al., 2011). Halvorsrud et al. (2016) defined four attributes for touchpoints: initiator, time, channel (medium) and trace (result or evidence).

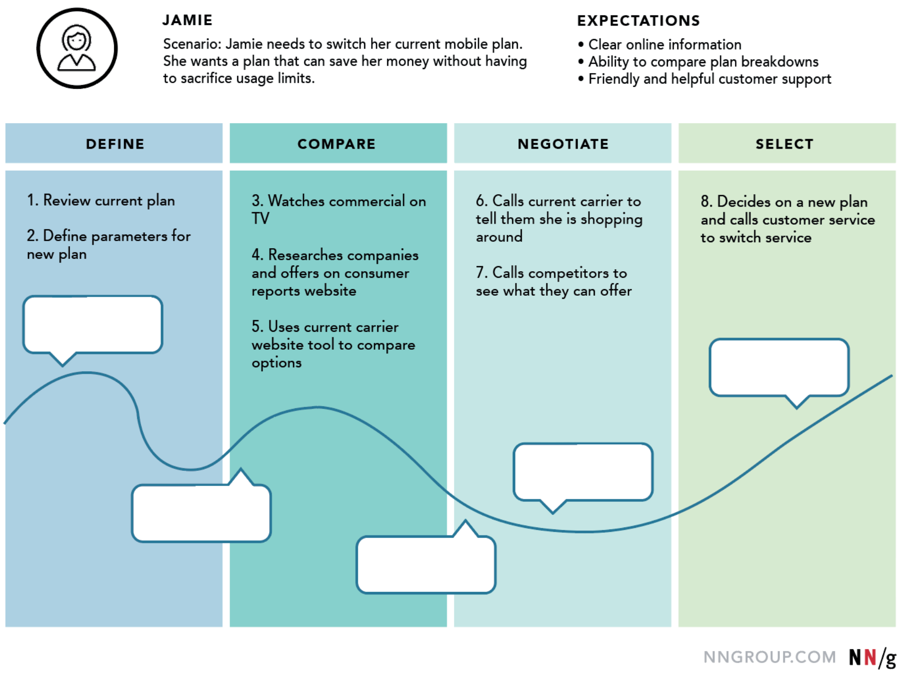


Figure 2.5. A schematic customer journey map of Jamie, who is switching mobile plans by Gibbons (2017).

Personas
Personas are “virtual users” (Hosono, Hasegawa, Hara, Shimomura, & Arai, 2009) that represent target users (Miaskiewicz & Kozar, 2011) to personify user characteristics for design and marketing (Sinha, 2003). Personas help mainly for focus, prioritisation and challenging assumptions (Miaskiewicz & Kozar, 2011). Designers create different types of personas, such as broad-scope marketing personas and targeted-scope UX personas (Flaherty, 2018).

Service blueprint
A service blueprint is defined as a visual diagram that shows the relations between different service components and processes (Gibbons, 2017) and the steps of a service delivery process (Halvorsrud et al., 2016). The perspectives of the user, service provider and other relevant stakeholders are incorporated in different layers such as the customer, front-stage, back-stage and support (Figure 2.6). The service blueprint identifies crucial service elements and processes, and can bridge cross-department efforts, such as defining responsibilities for these internal departments (Stickdorn et al., 2011).

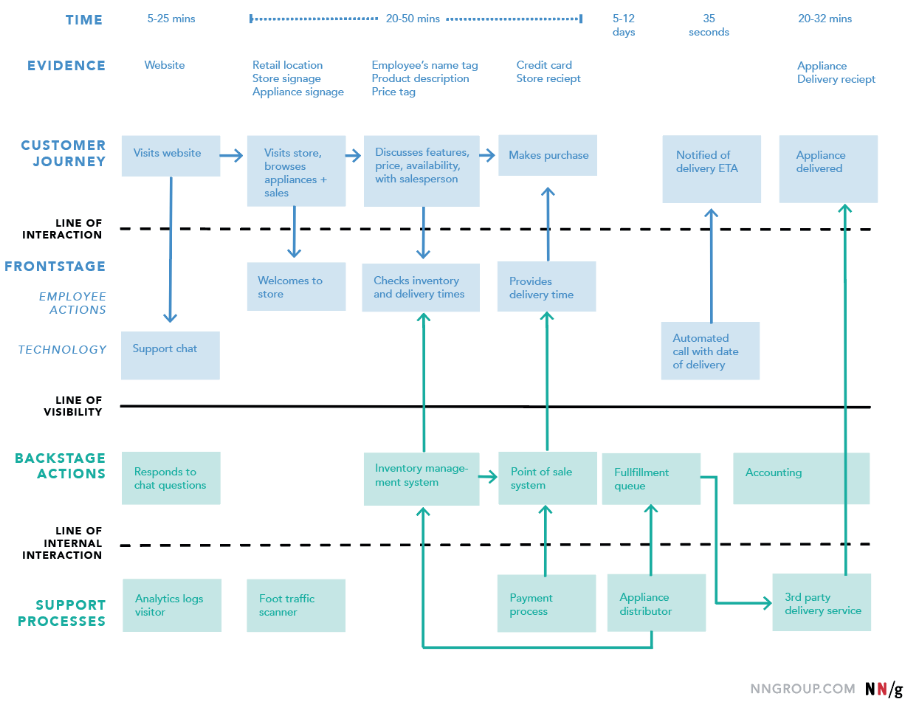


Figure 2.6. Buying an appliance service blueprint example by Gibbons (2017).

Shadowing
Service designers follow and observe people in their routine during shadowing. Designers witness problems at the spot, and this method exposes behaviours

which the user or stakeholder is unaware of (Stickdorn et al., 2011). Empathy is created in this process because designers observe real-time experiences.

Stakeholder map

Mapping the stakeholders provide a visual or physical overview of the players involved in the situation (Stickdorn et al., 2011). These maps are created to gain a top-level understanding of the situation, organisation and operations (Johnson & Henderson, 2002). They are useful for identifying opportunities and unbundling and re-building service offerings (Normann, 2001).

Workshops & participatory sessions

Experience-centric services should engage customers which could be achieved with user participation (Zomerdijk & Voss, 2010). With participatory sessions, also called workshops, users and stakeholders play a part in the design process with design thinking and co-design methods.

Other methods

Many other design methods exist and practised daily by service designers next to this small collection. The following list contains the honorable mentions: conceptual models (Johnson & Henderson, 2002), cultural probes (e.g. diary studies), mobile ethnography, expectation maps, design scenarios, storytelling, storyboards, enactment (service staging), miniature roleplaying (desktop walkthrough) and business model canvas (Stickdorn et al., 2011).

Chapter 3

Data Mining

That the amount and significance of data in our world grows, is overstated. However, it is not the data itself that is promising; it is what we can do with it. There is a gap between having data and understanding of it (Witten & Frank, 2005). Moreover, the goal is not to have data but to produce real value (van der Aalst, 2014a). Data mining provide techniques to extract knowledge from big data. This chapter will discuss the *Definition of Data Mining* (Section 3.1), related fields and a short overview of *Data Mining in practice* (Section 3.2).

3.1. Definition of Data Mining

Data mining is the process of automatically[1] identifying meaningful information or useful patterns from big data (Tan et al., 2006). Furthermore, it is a tool for explaining data and making predictions (Witten & Frank, 2005). The output should be meaningful, novel, useful, unsuspected and understandable (van der Aalst, 2014a). Data mining is a practical topic and could be described as a set of techniques for discovering and describing patterns in data of "substantial quantities" (Witten & Frank, 2005).

Data science and data mining can extract value from data and therefore are a key differentiator (van der Aalst, 2014a). Data is a valuable resource that produces new insights and competitive advantages because it adapts to the customer (Witten & Frank, 2005). The techniques of data mining "can be used to support a wide range of business intelligence applications" such as a better understanding of the needs of customers, customer profiling, workflow management and store layout (Tan et al., 2006, p. 1). The support of data mining in the field of design is extended in *Design and Data mining* (Chapter 5).

Related data sciences

Although data mining and data science are sometimes used interchangeably, they are not equal: data mining is part of data science. Data mining is the process that implements the techniques and algorithms and is involved in the "actual extraction" (Provost & Fawcett, 2013).

[1]'usually semiautomatic' according to Witten and Frank (2005).

Data science is a discipline, such as mathematics and computer science (van der Aalst, 2014a). Data science includes more than the applied extraction of knowledge or its representation. It embodies the fundamental principles that support and guide the extraction of knowledge from data (Provost & Fawcett, 2013). Data science contains additional mining techniques (e.g. process mining) and contextualising fields (e.g. visualisation and statistics) (van der Aalst, 2014a). The primary data sciences discussed in this thesis are:

Data Science Field concerned with the support and guidance of the extraction of knowledge from data (Provost & Fawcett, 2013).

Data Mining Process for extracting useful patterns from (tabular) data (van der Aalst, 2014a).

Process Mining Process for extracting useful knowledge of processes from data (logs) (van der Aalst, 2014a).

3.2. Data Mining in practice

This short overview of the practical side of data mining contains a global flow of a *Data mining process* (Section 3.2.1). Next, a few prominent *Data Mining techniques* (Section 3.2.2) will be discussed.

3.2.1. Data mining process

Data mining process starts with determining the mining goal or problem. For example, assigning a given Iris flower its species class ('Iris setosa', 'Iris virginica' or 'Iris versicolor') is a classification problem. Next, the data scientist data that matches the problem by recording or collecting from existing databases. This raw data contains mistakes, inconsistencies and must be pre-processed (cleaned and prepared) before applying the mining technique(s). Figure 3.1 shows the preparation of data.

Data mining problem

Task or question to be solved.

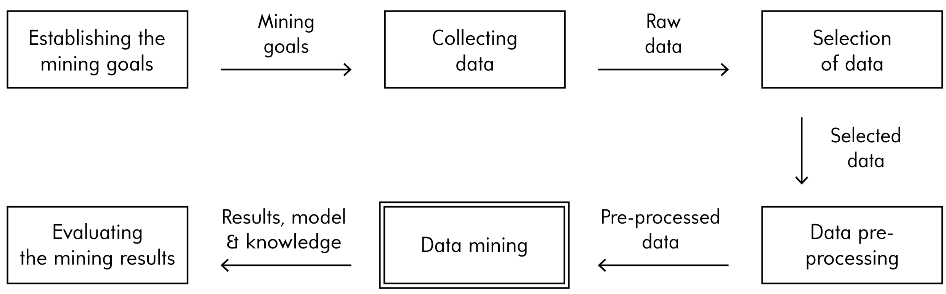


Figure 3.1. Knowledge discovery process of data mining based on Hui & Jha (2000).

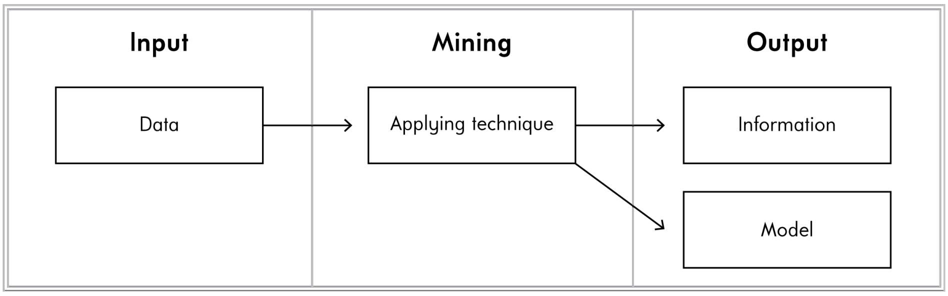


Figure 3.2. The actual process of data mining.

After preparing, the technique can be applied. The mining technique requires an input and results in an output (Figure 3.2).

Input

A dataset contains multiple data points that represent instances by values of features or attributes. Furthermore, the size of the dataset (the amount of data points) is substantial (Witten & Frank, 2005). In general, the datasets are labelled and could be represented in a tabular form (e.g., Figure 3.3).

Labelled data

Data where the data-points have tags called labels, which can be seen as the correct answers.

For some problems and techniques, the data scientist divides the data set into a training and test set. Then, a part of the data is preserved for learning and the other part to test the learned solution with different instances. The quality of the input data is essential, as van der Aalst describes: "Fancy analytics without suitable data are like sports-cars without petrol" ((2014a), p. 5).

Output

Depending on the problem and techniques used for data mining, the output differs. An answer could have the form of text-based statements, association rules, visualisations or other structures (Witten & Frank, 2005). The model itself is also an outcome that data scientist uses for predicting and solving new instances. The data scientist checks the trained model with the test dataset, and the results include statistical scores, such as accuracy and precision measurements.

Finally, the data scientist evaluates the results of the mining and continues with an iterative process by adjusting the pre-processing and/or mining for better results.

	Identification	Features			Classified in classes
	Id	Length	Width	...	Class
	1	8.24134	3.33064	...	blue
Data point	2	5.45142	6.86552	...	red
	3	6.87654	5.141567	...	blue
	...	...	...	...	...

Figure 3.3. Example of a basic tabular dataset.

3.2.2. Data Mining techniques

This section will provide a overview of data mining and machine learning problem categories and techniques. There exist a couple of main data mining problems: classification, association, regression and cluster analysis (Tan et al., 2006; van der Aalst, 2014a):

Classification is the task of assigning instances to predefined categories. For example, placing mail into the spam of the inbox folder.

Association analysis finds relations (association rules) in a dataset containing sets of items, such as market basket transactions. For example, the purchase of diapers has a strong relation to buying beer.

Regression aims at finding and estimating relations between dependent and/or independent variables. An example is a correlation between the amount of sunlight in the office and a decrease in sick leave.

Cluster analysis divides instances in meaningful and/or useful groups. For example, splitting a large group of target users based on distinctive features without defining groups size of group features.

Data mining techniques are suitable for one or more of these problems. Many techniques and variations exist and are practised daily by data scientists. The following small collection of techniques appear in this thesis.

Hierarchical clustering

With hierarchical clustering, the clusters are defined by a hierarchical tree-like graph or dendrogram (Figure 3.4). This tree can grow agglomerative (bottom-up, ascending) or divisive (top-down) (Tan et al., 2006). The algorithm measures the distance between instances and clusters to determine which instances create a new node.

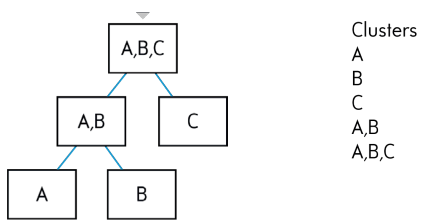


Figure 3.4. Example of hierarchical clustering the instances A, B and C.

k-means clustering

Clustering by the *k*-means algorithm is based on the idea that the mean of a cluster that functions as a prototype (Tan et al., 2006). A new instance is placed into one of the *k* groups with the nearest mean for that instance (Figure 3.5).

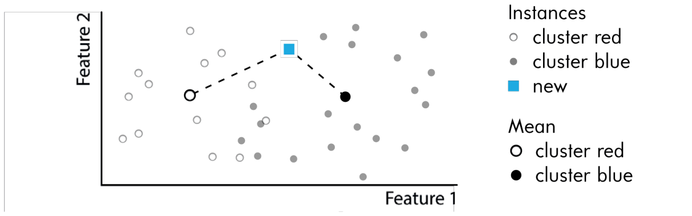


Figure 3.5. Example of k-means clustering with k=2. The new instance ■ is placed in cluster ●.

Decision trees
The decision tree is a one-directional flowchart of nodes, where each node contains binary-partitioning threshold (separates into two choices). An instance passes through the tree and ends up in a leaf (end node) with an associated class (Bishop, 2006). Figure 3.6 displays an example of a decision tree.

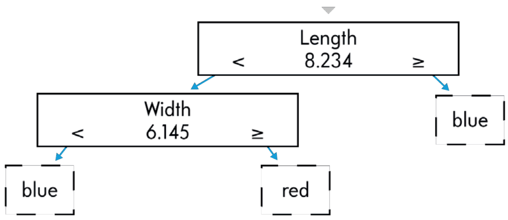


Figure 3.6. Example of a decision tree to classify *red* and *blue*.

(Artificial) neural network
Neural networks (NNs) are a machine learning technique that learns by adjusting weights of connections in a graph of neutrons (Bishop, 2006). In the case of Generative Adversarial Networks (GAN), two neural networks work together to respectively generate and evaluate new data based on the original data.

***k*-nearest neighbours (k-NN)**
The algorithm k-nearest neighbours classifies by assigning a new instance to the class (cluster) that occurs most among the k nearest neighbour instances (Bishop, 2006) (Figure 3.7). The explanation of the decision is relatively high (Kononenko, 2001) because near and probable instances are presented.

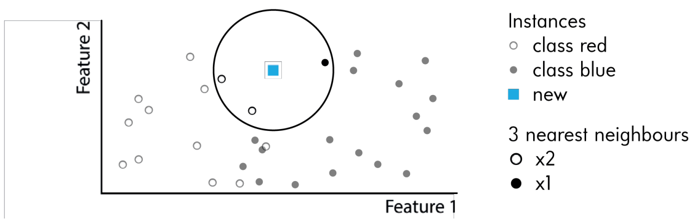


Figure 3.7. Example of k-nearest neighbours with k=3. The new instance ■ is placed in cluster ○.

Linear & logistic regression
Linear and logistic regression are statistical algorithms that models the relationship between variables with a linear and respectively sigmoid function (Bishop, 2006) (Figure 3.8). The logistic modelling is more popular than linear regression and describes the combined effect of several attributes (Kleinbaum, Klein, & Pryor, 2002).

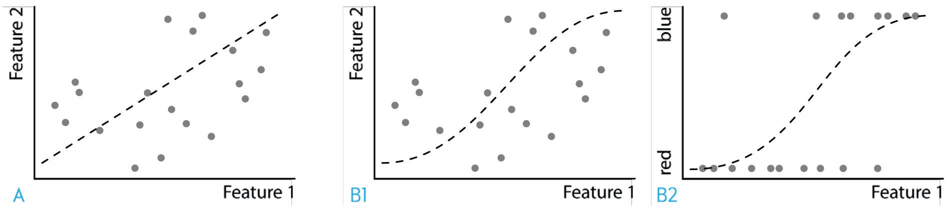


Figure 3.8. Example of linear regression (A) and logistic regression with numeric (B1) and nominal feature (B2) on the y-axis.

Factor analysis
Factor analysis is a statistical method that finds linear-Gaussian correlations within observed variables to describe unobserved variables called factors (Bishop, 2006). It could be used to reduce features or find correlations between features. For example, math and chemistry test results of students (observables) are a single factor that is related to the mathematical intelligence of students (factor).

Markov model
The Markov model represents states of partially or fully observable systems and can measure unobserved variables and predict next states (Bishop, 2006). The transition diagram displays these states and their transitions (Figure 3.9).

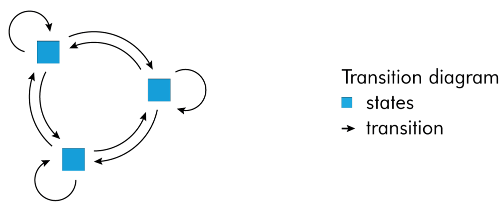


Figure 3.9. Transition diagram of an example Markov model with three states.

Part II

Research process

Chapter 4

Research process

This study researched how data mining can support the service design process through design research. Design research is "theory construction and explanation while solving real-world problems" (Oliver, Reeves, & Herrington, 2005, p. 103) and characterises in applying design principles to render plausible solutions to complex problems. According to Oliver et al. (2005), design research includes a reflective inquiry to test, refine and reveal new design principles with both researchers and practitioners.

During this research process, I examined the data mining supported service design process by developing a guide to concepts of data science methods for service designers. In the development, both academic and practical designers were involved with user-centred activities. The current chapter will describe and reflect on the research process that led to the concepts of these methods.

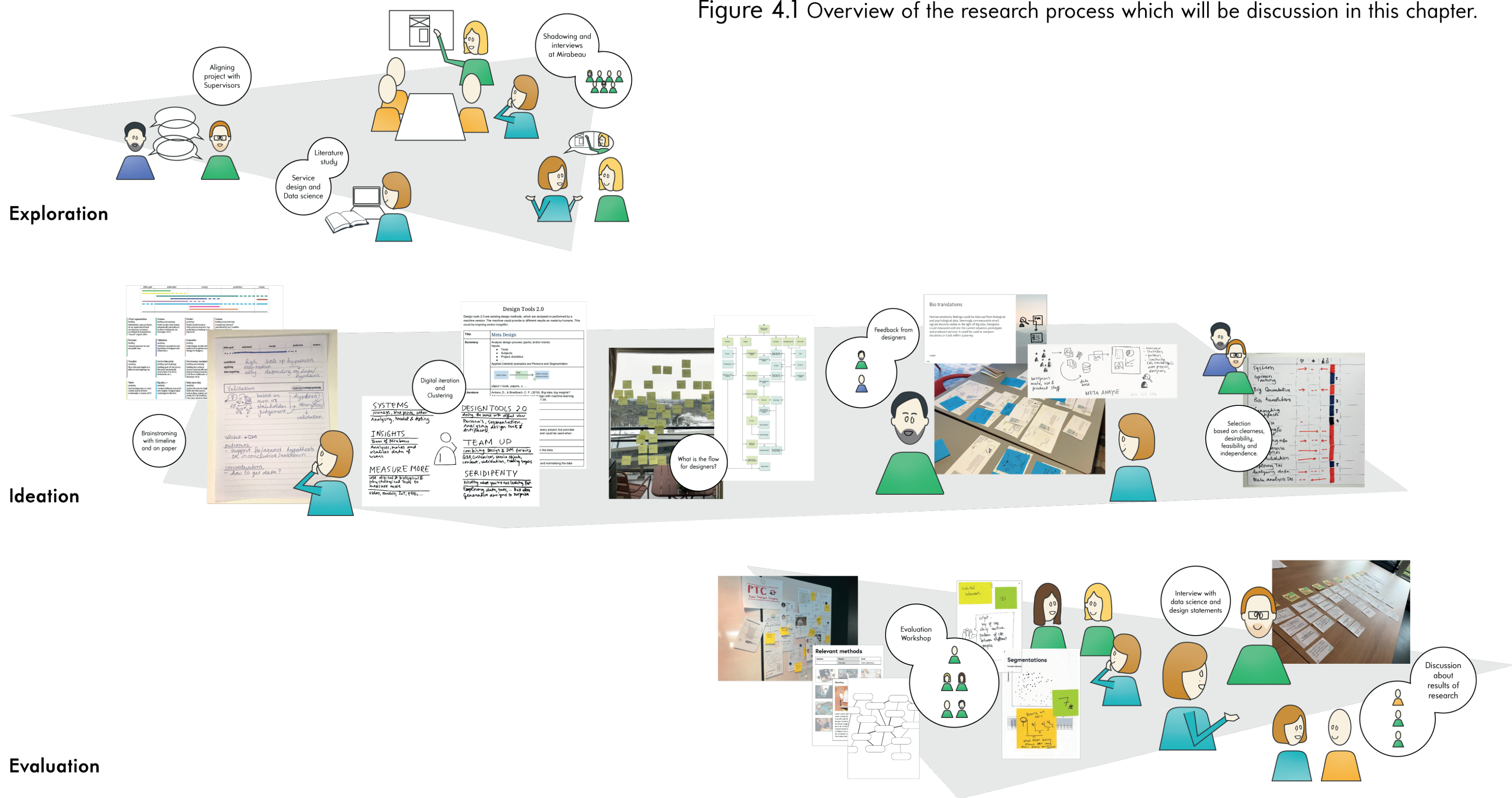
The research process was an iterative process of converging and diverging activities that resulted in a guide to concepts of the methods. We can distinguish the following main phases in this research process: exploration, ideation and evaluation (Figure 4.1). During the stages, iterations evolved the methods by emerging, splitting, merging, terminating and changing (Appendix A3.1).

The first phase of the research, namely *exploration*, focused on the characteristics, possibilities and opportunities of both fields: data mining and service design. The goal of this phase was defining the research areas, understanding designers and data scientists and create a mental framework. Shadowing, interviewing, and literature review were the essential activities in this phase.

These opportunities grew and were pruned in the *ideation* phase, resulting in the guide to data science and team methods. Refining the ideas included designer participation, case studies and/or speculative cases. The main activities in this phase consist of brainstorm methods, paper tools and feedback sessions with designers.

The *evaluation* phase tested the usability and desirability of the methods and conclude overall findings from the design research. Workshop sessions with designers, self-reflection, discussions and a panel interview substantiated this phase.

Figure 4.1 Overview of the research process which will be discussion in this chapter.



4.1. Exploration and orientation

The exploration phase centered on the following subquestions, which are addressed in *Answers on the research questions* (Section 8.1):

1. What does the Service Design process need?
2. What can Data Mining offer?

First, the research started with reviewing service design in its academic and applied context. The literature review provided insights into the goals, definitions and background of service design, while interviewing and shadowing service/interaction designers at the digital agency Mirabeau showed the implementation of service design.

Shadowing took place in five projects in various stages of the design process for one or multiple days (1 day, 2 days, 1 day, 1 day and 6 weeks) at Mirabeau's or their clients' office. The designers were very open and invited me to meetings, kick-off sessions or join applying a design method. During these activities, they answered questions about the purpose and goals of their actions and alternative approaches.

At the end of the shadow sessions, I conducted interviews to discuss their motivations. A total of seven designers participated in these interviews one-on-one or one-on-two. During these interviews, they talked about the boundaries of their work, interaction versus service design and the difficulties they face. The answers provided insight into how they fundament their design (e.g. user research and stakeholder management), how they experience their work, and how the shadowing day relates to a typical working day.

In conclusion, the practitioners at Mirabeau showed their design process, allowing for an analysis of their methods, needs and problems. Results of these insights are useful for understanding why specific methods are applied. *Design at Mirabeau* (Section 2.2.2) describes Mirabeau's way of working.

With a better understanding of service design, the literature study expanded to data mining, mixed-methods and data science for design. Other related fields that are joining forces with data mining were included in this study, such as product design (Tuarob & Tucker, 2015), manufacturing (Köksal et al., 2011), marketing (Murray et al., 2018) and ethnography (Zheng, Hanauer, Weibel, & Agha, 2015).

In the meantime, pitching the research in the organisation and external events supported in a clearer view of the study and provided feedback and ideas from different disciplines. Their feedback was on a very high level but resulted in valuable relations for later in the process.

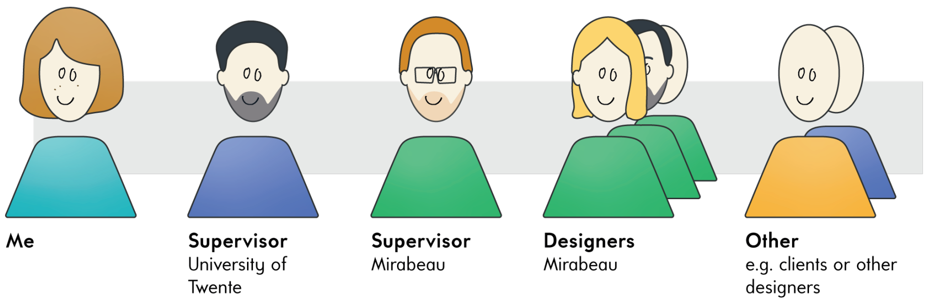


Figure 4.2. People involved in the research process. They will appear in the illustrations of this chapter.

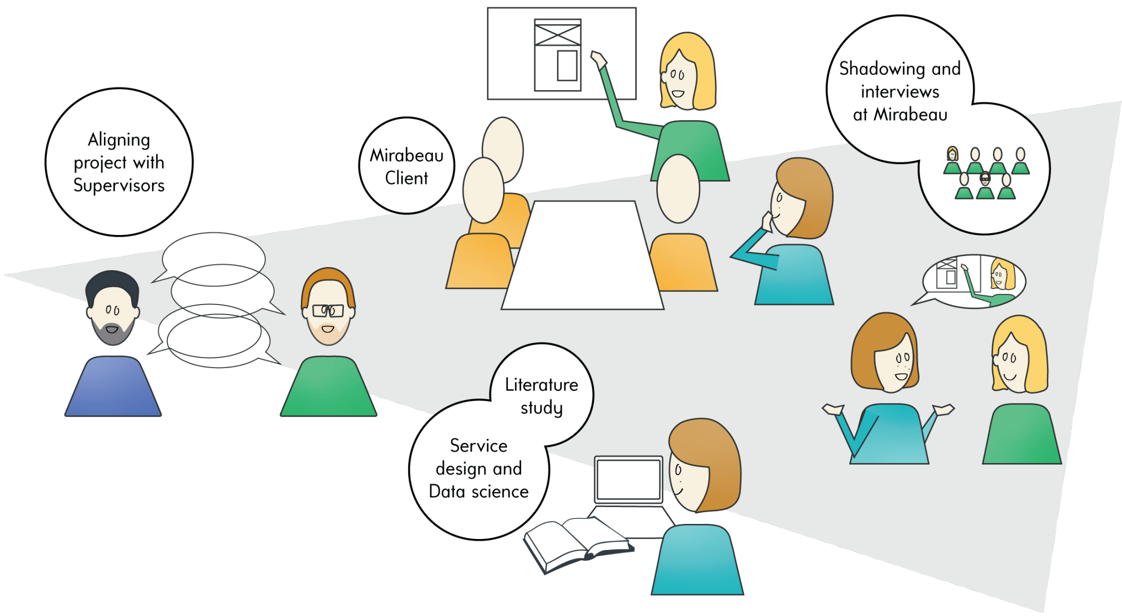


Figure 4.3. Main activities in the explore phase.

4.2. Ideation

During the ideation phase, I developed the guide to concepts of existing data science methods for service designers in an iterative process. From brainstorming emerged different "method cards", which are paper and/or digital summaries of a concept with various attributes. The cards wend through rounds that expanded the concepts or criteria that narrowed the scope. One of the requirements was desirability, which I tested during the feedback sessions with designers. In the end, 11 of the 34 individual methods endured. Appendix A3.1 displays a summary of this evolution.

Method cards

The first ideas resulted from an individual brainstorm session, where the concepts related to the design process. Ideas sparked from either the design perspective or the data mining field, but should fit both (Figure 4.4). For example, designers deal with many assumptions based on their expertise and or qualitative sources. Maybe data mining can help validation some of these assumptions? The ideas were collected in a digitised overview (Appendix A4.4), which changed over time, but the ideas remained abstract.

Line of thought			Example
What do designers want/need?	»	How could data mining help?	In the understand phase, it is useful to have an overview of users groups. Most segmentations are forced groups made by humans. Could automated groups, based on behaviour, be insightful?
What tools/methods use designers?	»	How could data mining help?	Designer deal with many assumptions based on their expertise and or qualitative sources. Maybe data mining can help validation some of these assumptions?
What has data mining to offer?	»	How could designers use this?	Data mining can help to predict future events. Maybe data mining can predict something that helps with prototyping?

Figure 4.4. Line of thought during the first brainstorm sessions.

For the next step, a creative flow was necessary to do two things: a) generate more ideas and b) refine existing ideas. An ideation method was needed that makes ideas while addressing their attributes. As a solution, I developed paper fill-in cards. Going back to paper provided a more creative atmosphere. These first 'methods cards' engaged in thinking about the ideas in a structured, yet open way by leaving wide open spaces with hints for attributes (Appendix A4.2).

The attributes were requirements for the concepts and included the design process, the usefulness for the designer, difficulty of applying, data requirements, title, and data mining type. During the use of the cards' 'outcomes' and 'considerations' were added. These additions, together with the title description, helped answer what the method is and the direct results are. The data mining type proved useless because they were too general. The end result was 18 separate cards.

After creating, all cards were critiqued. Which cards are vague, weak or redundant? Which cards are promising or useful? The methods were subject a round of refinement, removal, combination and regrouping.

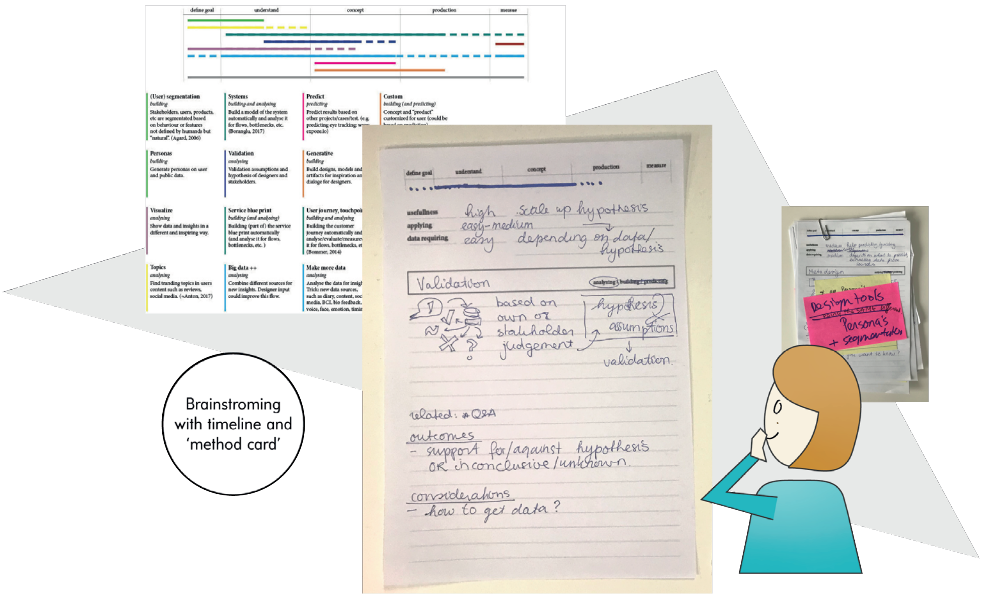


Figure 4.5. Brainstorming for generating ideas (Appendix A4.4 and A4.2)

The groups of paper cards became six categories, which stand for the overall mechanisms of the methods (Appendix A4.5). After iterations of improving the methods and categories, the four categories remained. The methods of the two dissolved groups moved to more suitable categories. For example, *Insights* and *Measure more* merged. The final four categories are discussed in *Data mining methods for service designers* (Chapter 6).

Systems	Analysing, modelling and testing of systems from service design such as customer journeys.
Measure more	Tools to extract more or new information from users than familiar design and user research tools. This category became *User research*.
Insights	Tools for assisting in user research. This category merged into *User research*.
Design tools 2.0	Tools based on scaled-up design methods. These concepts moved to categories with less generic names.
Team up	Methods for better or more effective collaboration between design and data mining. This category was renamed to *Collaboration*.
Serendipity	Provide inspiration or surprise by exploring.

The paper card grew into a new digital version (Figure 4.6). This digital version could benefit from its different media that is content-flexible and online shareable. Although the text and scientific background improved in this version, the creative flow stopped. They lost the prototype feeling, which made it harder to share and discuss with fellow designers. This issue was solved when the feedback sessions used physical, minimalistic cards with sketched examples of use cases (discussed on page 34).

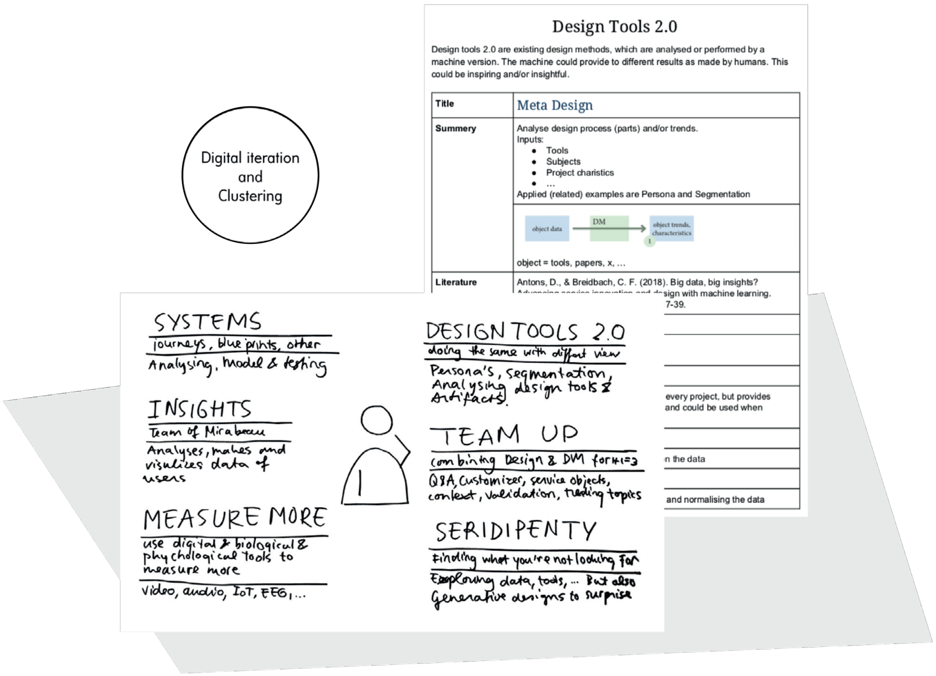


Figure 4.6. The first categories and example of a digital card (Appendix A4.5)

The methods should lead to actual use by designers. In the meantime, the ideas should also be shared, discussed and evaluated with fellow designers. The next step was to put the methods from the perspective of the designer. What do they mean to *the designer*? The method concepts were soon subject to verification by the designers and needed preparation for this. The new overview should check if the methods are ready for the feedback session.

The next brainstorm was set up as a challenge: how could designers end up at a method from the question “What are you looking for?”. This lead to a flow diagram (Figure 4.7 and Appendix A4.6). This view fitted the methods to terms familiar to designers. Furthermore, the context and subjects of the data mining techniques were now defined. For example, *Bio translations* could interpret many signals, but now it should be used to understand emotions. This process again resulted in refinement, removal, creation and reshuffling of methods.

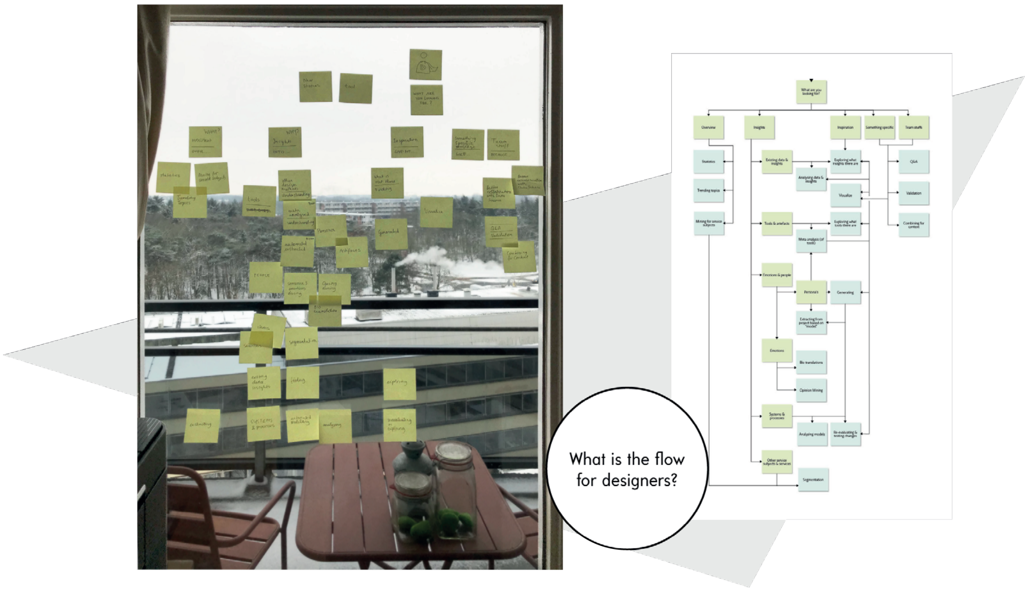


Figure 4.7. Connecting the needs of designers and methods (Appendix A4.6)

The method scores

As part of the method critique, the concepts were repeatedly quantitative scored. The concepts and research were in development and the score data expanded and updated subsequently. Appendix A5.2 contains the latest values of the final methods. The score data was useful to compare the concepts to each other, force refinement on certain areas and apply criteria. It formed the base for visualisations, such as Figure 8.1 and Appendix A5.

The 'method card' attributes formed the base for the first scores. This were the applicability in the design phases, the technical difficulty and expected desirability. Later, the methods showed more differentiating factors and I examined those in more detail. This resulted in new attributes: the main purpose, data subject and qualitative-quantitative scales. The expected desirability was removed when all the methods met the final selection criteria (discussed on page 36).

Scoring was done regularly, manually and based on personal judgement. Originally, the scale was a eleven-point scale from 0 to 1. Defending small differences was difficult and therefore the scale changed into a seven-point linear scale.

Score scale

Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
1	2	3	4	5	6	7

Feedback sessions

The preparation of the feedback sessions started, now the concepts and context of the methods were ready to share. For the session, the methods were transformed into a new minimalistic card (Appendix A4.7). To process as many methods in one sitting, the methods needed to be communicated efficiently without distractions. The minimal card contained a title, short description and small visual DM diagram. The diagram was a personal reminder, and there were no expectations that non-technical participants would understand them. Although I made 24 cards, only 15 cards proceeded.

The text-based cards were very generic and combined with sketches of examples of use cases (Appendix A4.8a). These sketches were made previously in the process, and I also reused the text from the minimal card.

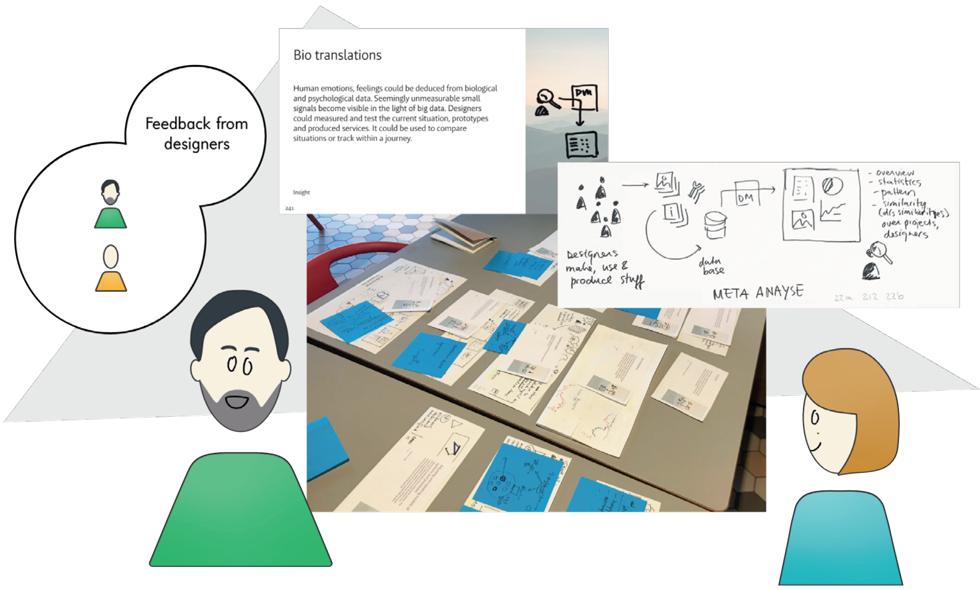


Figure 4.8. The design feedback sessions used the minimal card (Appendix A4.7 and A4.8)

The feedback sessions were two separate sessions of 60 and 100 minutes with a designer from Mirabeau (Designer A) and designer from outside Mirabeau (Designer I). The main goal of the feedback was to test if the methods were clear to the designers and when/why they would use it. The semi-structured interview was mainly verbal but made use of the cards and sketches mentioned earlier. Feedback from the designers was recorded with permission and conclusions were written on notes.

During the sessions, it became clear how dependent the participants were on the facilitator. This dependence made the sessions difficult. The methods were abstract and still too technical. Fortunately, the interviewees were interested, engaged and made an effort of understanding the methods. They needed, however, relatively much time and frequently asked for clarification. The interview provided in this way insights to the blind spots of the methods and their descriptions.

The notes from the session with Designer A stayed on cards during the next session with Designer I (Appendix A4.8). The notes helped improve the explanation of the methods and test these improvements with the second designer as a mini-iteration. Although reusing the ideas of Designer A could influence Designer I, the second designer caught up faster and was not afraid to provide a personal perspective to the methods. In more detail, Designer I tend to talk mostly about the visual opportunities of the techniques.

In conclusion, the feedback sessions were an assessment of the methods and provided feedback on the methods, their description and their use. Secondly, the sessions provided insights into the difficulty of engaging abstract and technical concepts to designers.

Final selection

The research reflection meeting with the supervisors was after the design feedback sessions. During this meeting, we discussed the research process that had addressed different aspects of the methods so far: the technical feasibility of data mining and potential desirability for designers. Since the original planned applied case was cancelled, the technical depth lost priority. The adjusted research focus was to connect the methods to the designers' daily lives. The scope would aim at the purpose of using design methods, such as gaining a useful outcome. The methods would remain concepts but should include viable next steps.

Another conclusion of the meeting was that methods with the independence of the data scientist, were more pragmatic. A method without dependence on data science results in more effective workshops. This is a practical reason and not because independent methods are preferred.

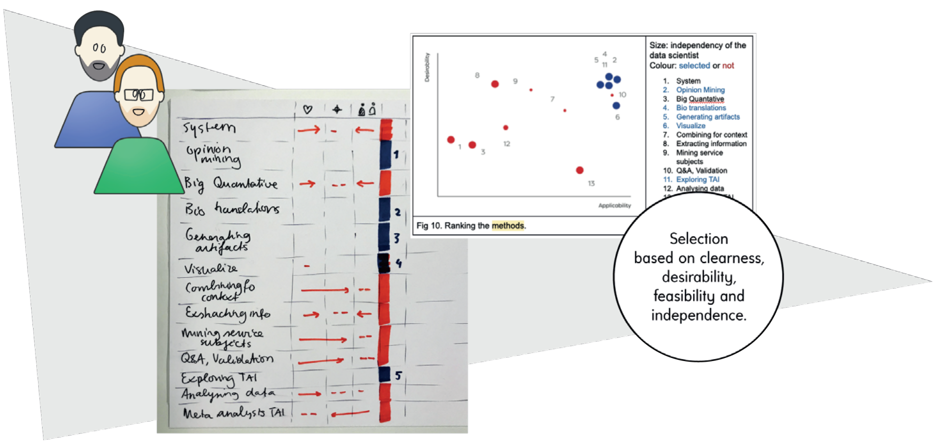


Figure 4.9. The research reflection meeting and selection of final methods.

Eleven final methods derived from the insights from the design feedback and the requirements of the new scope. These methods are also presented in *Data mining methods for service designers* (Chapter 6). The concepts of the methods met the following criteria:

1. Clear	What and how the method works should be evident.
2. Desirable	The method meets the needs of the designer and fits the design process.
3. Feasible	The method includes a theoretical technical foundation.

4.3. Concept evaluation

In the last phase of the research process, the methods went through an assessment in the design critique workshops. The preparations included the development of the hypothetical PTC case and an entirely new form of the method concepts: 'outputs'. An output is a hypothetical result of applying the method in the hypothetical case. Per method, multiple directions were implemented to test the various possibilities of a method. The workshop itself was tested in a pilot and conducted after improvements with two sets of designers.

PTC case

The fictive PTC case featured the fictitious company 'Public Transportation Company'.

The research concluded utilising discussions and a panel interview about the results. The discussions were one-on-one meetings in which we discussed the overall conclusions of the study and future steps. The panel interview used 'panel statements' about design and data science to formulate relevant findings.

Design critique workshops

All methods were repeatedly criticised during the ideation phase. They were part of the feedback sessions with the designers and met the three criteria, as mentioned in the *Final selection*. I selected five methods for the more detailed evaluation of the design critique workshops (Figure 4.10). Due to time constraints, the evaluation of all methods is not feasible, and future research is needed to cover the excluded concepts as well. Selecting methods for the evaluation workshop depended on an additional criterium to the final criteria (Section 4.2):

4. Independent	The method should be explainable without dependence on how the data science works. The workshops are more effective when the designers only have to relate to their part.

The *Collaboration* category was excluded due to the collaborative nature of the methods. For similar reasons, the *Systems* category was technical heavy, and designers would highly rely on the facilitator of the workshop.

As discussed earlier, the concepts showed technical feasibility and potential for desirability, but applied desirability and viability was not validated yet. The evaluation workshop, also called design critique workshop, was designed to evaluate the reason to use the methods: the outcome.

Presented in	thesis	workshops		thesis	workshops
Opinion mining	✓	✓	Systems	✓	-
Bio translations	✓	✓			
			DM on request	✓	-
Meta analyse	✓	-	Q&A and Validation	✓	-
Explore Tools, Artifacts and Insights	✓	✓	Combining for context	✓	-
Generating artifacts	✓	✓	Visualise	✓	-
Segmentation	✓	✓			

Figure 4.10. The methods that are discussed in the thesis and in the workshops.

Instead of presenting methods, we would discuss the result of an applied method during the workshop. This approach would lead to more concrete feedback than the abstract and technical cards of the previous design feedback sessions. The applied form, called ‘output’, was placed in the context of the fictitious client called ‘Public Transportation Company’ (PTC). In the workshop, the designers imaged working for this project to develop a new or improved service.

The methods applied to the PTC case with different variations to discuss the various possibilities of one concept. For example, the *Bio translations* method can interpreters facial and other user signals. Which signals is not crucial at this stage, but it does matter whose emotions and why they are measured. During the workshop, designers could add their own output versions.

In contrast with the textual methods cards, the outputs were mainly visual for easy access. A playful colouring page style expressed a ‘friendly’ font, think lines, illustrations and, if needed, bright colours. The five methods resulted in 15 outputs (Appendix A7).

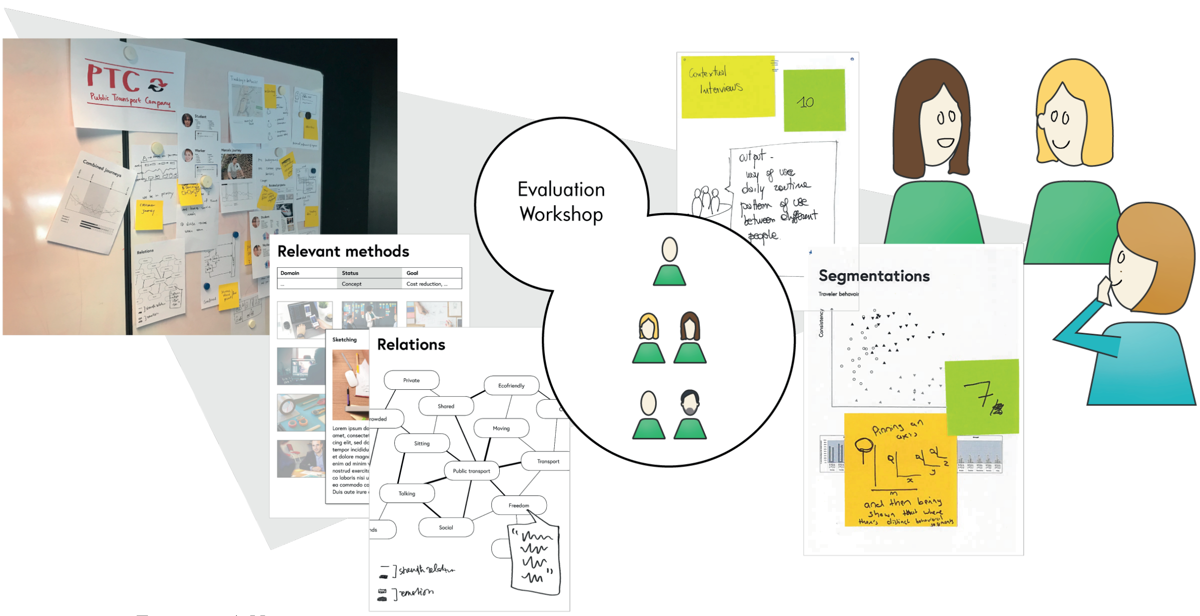


Figure 4.11. The evaluations workshops addressed the desirability and usability of five methods (Appendix A4.11 and 4.12)

Before conducting the workshops, I run a pilot workshop with one designer (Designer K). Appendix A4.9 describes the setup, and the main activities were:

Warming-up Provide context and clarify the concept of 'output' by asking for their own top 5 design methods. For these methods, the participant made outputs in the context of the PTC case.

Evaluation The data science outputs are evaluated per method. The participant tells how and why he/she uses the output and decides which to keep for the case.

The warming-up exercise eased introducing the unfamiliar data science methods and outputs. Additionally, the designer was reminded of their design process and daily work. When presenting the data science outputs, it was clear that the designer related the data science methods to existing ones because Designer K spontaneous ordered the own and presented outputs chronological.

The feedback, including personal preferences, was very informative. The interview revealed needs and fears, but the question "Would you use this method?" was answered mostly "Yes". Comparing the methods and variations of outputs was still challenging and needed improvement in the next workshops.

The pilot modelled the final workshops. The two sessions with each two participants (Designer J & Designer D and Designer F & Designer A) had some changes (Appendix A4.10). Improvements were: 1) updating instructions and time schedule, 2) change prepared questions for interview parts and 3) add grading assignment to the outputs.

Grading After the warming up and the evaluation, the participants add a grade (0-10) to the outputs (Figure 4.12). The grade symbolises how likely they would use it in their next 'standard' project.

The grades could be used to compare the preferences per designer. No interesting differences between the data science and the top five methods were expected, since the current top five would logically have the highest grades. Surprisingly, the data science grades were not low (N=36, M=8.24, SD=1.64), especially compared to the own top five (N=19, M=8.84, SD=1.30)[1]. The designers sometimes preferred data science methods over their top five (Appendix A4.3).

The techniques were applied to different data in various contexts and the insights gained from the workshops aided focus. Emotion- or experience-based variations were favoured (applicable to four of the five methods). During the discussions, the designers discussed their perspective, needs and fears. For example, the fear that the output contains a low quality: Designer A said "Don't give me noise. Because you can show me much data that consist of pure noise".

[1] No significant difference according to Welch t-test: t=-1.50, p=0.14.

(a) Method of a designer (b) Presented method

Figure 4.12. Examples of a) top five and b) data-mining based methods with a grade. The designer suggested a custom axis for the presented method.

The workshop challenged the designers to think about their way of working critically. For instance, two designers argued about the implications and relevance of user research conducted by only one person.

Some of the discussed scenarios were unrealistic. Unlimited scenarios can reveal particular wishes but predict less accurate the real situations. Therefore, the facilitator proposed more realistic scenarios with restricted resources to force the designer to make priorities.

Another observation was that the designers commented on qualitative and quantitative insights, although the facilitator never mentioned this distinction. Designer K said the struggle with the "effective" quantitative research and its integration with the human-centred focus of designers. Other designers also expressed the wish to learn and use more quantitative data.

The insights of the workshops are presented in 'design critique' sections of *Data mining methods for service designers* (Chapter 6).

Discussions and panel interview

The evaluation phase concluded with a set of discussions and a panel interview.

The discussions were one-on-one meetings with a service designer (non-Mirabeau) and two coworkers from Mirabeau. During the sessions were the overall conclusions of the research and future steps for designers and projects discussed. The discussions showed various angles of the data science methods, such as 1) the design process 2) tools vs teams and 3) data maturity of client. Furthermore, other implications were reviewed, for example, collaboration, the start of a project with user research and/or data science, and how to sell such projects.

The insights from these discussions were used to improve the theory of *Design and Data mining* (Chapter 5) and easy accessibility of the methods with the overview angles.

The panel interview was designed to conclude a vision about how data science can support service design. The preparation included organising statements about design, data science and user research. The 45+ statements were gathered from four practising or academic designers, and divided into groups with topic and priority. The facilitator interviewed me based on these statements, and we discussed in total, 19 statements (Appendix A4.13). Examples are:

- "Designers should understand -and partially be able to do- data science."
- "Data mining will only help in the *understand* phase."

The interview finished with one-sentence replies on the research questions. The conversation forced formulations out loud, and time constrains ensured short and relevant answers. The formulated theories and conclusions were used to structure the *Conclusion* (Chapter 8).

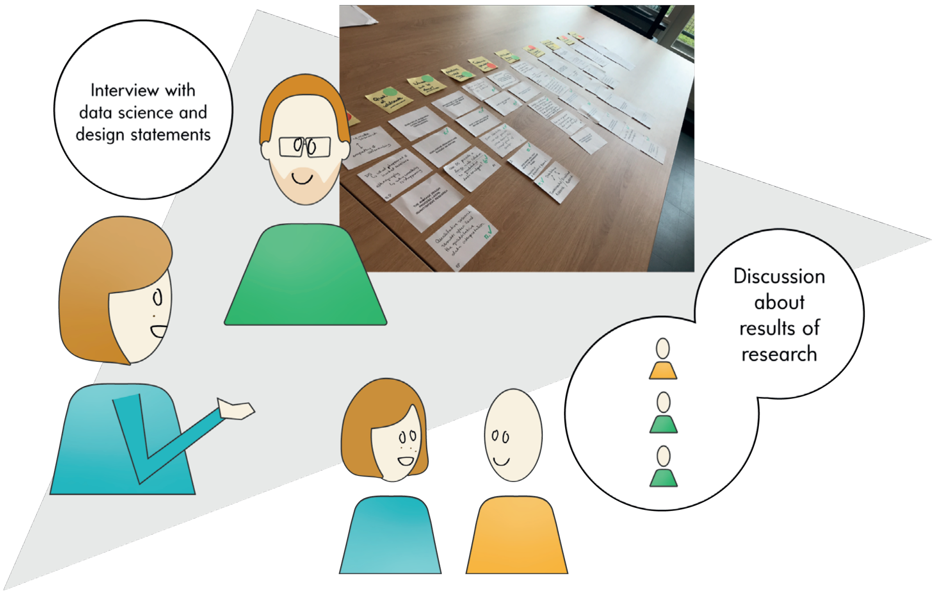


Figure 4.13. Discussions within and outside Mirabeau about the results fo the research. The discussions inspired the panel interview for 'statements', which structured the interview (Appendix A4.12 and A4.13).

Part III

Design and Data Mining

Chapter 5

Design and Data mining

Data mining has already shown to be useful in design disciplines, for instance, product quality improvement (Köksal et al., 2011), product characteristics (Tuarob & Tucker, 2015) and marketing (Murray et al., 2018). This chapter will discuss why data mining could support designers and more specific service designers. It answers where the opportunities lay for both design and data mining, how organisations mature in this field, and what the challenges will be when we collaborate. The next chapter, *Data mining methods for service designers* (Chapter 6), presents concepts for applying data science in design projects in more detail.

5.1. Opportunities

This section discusses the opportunities for data mining to aid designers by looking at the service designer as an user researcher and domain expert. Both roles provide a perspective on the needs of the designer and the contribution of data mining.

5.1.1. Method triangulation

Data

Factual statements or output.

Insight

Understanding formed from analysing data/information.

Information

Human representation of a collection of data.

Most opportunities for data mining to support the designers are based on providing easier, new and/or different information. Knowledge is fuel for service designers since they "organise, share, discuss and make sense of the data they collect to generate insights" (Costa et al., 2018, p. 165). With user, foundational and directional research, designers gather information from different sources: stakeholders, users, systems, teammates, books, each other, et cetera. The information-gathering activities continue throughout the design process, such as co-creation, prototyping and testing.

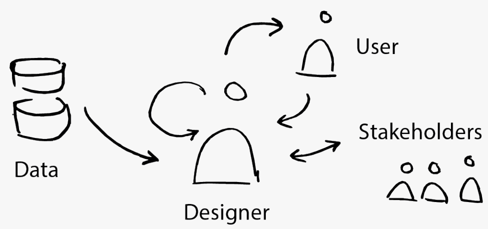
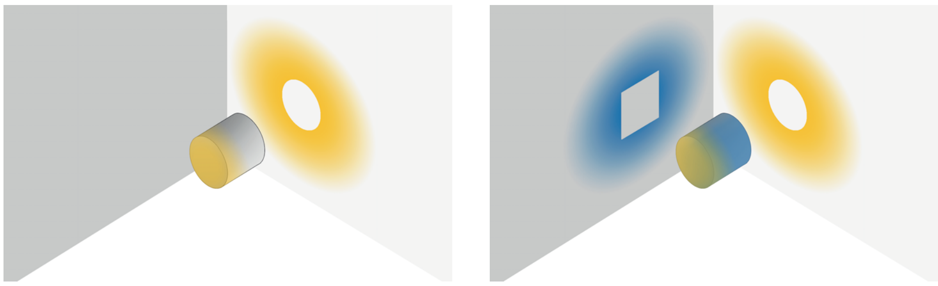


Figure 5.1. The designer as information gatherer

Designers use design and analysis methods for acquiring information and generating insights. A variety of methods and sources is vital to ensure their applicability and quality in a range of projects. Moreover, applying multiple methods increases the validity of the results. Every single method has weaknesses and limitations that can mitigate with method triangulation (Jick, 1979; Turner, Cardinal, & Burton, 2017). With method triangulation, for example mixed methods, the validity increases by decreasing the variance of the methods (Jick, 1979). Even a single method with reliable statistical results preserves its limitations while observing from a single angle (Figure 5.2) and lacks the “complete, holistic, and contextual portrayal” of triangulated observations (Jick, 1979, p. 603). An example of a strong combination of methods is integrating quantitative and qualitative findings (Jick, 1979; Creswell, Plano Clark, Gutmann, & Hanson, 2003).



(a) Similar to a light beam, a single method reflects only one side.

(b) However, method triangulation observes from multiple angles.

Figure 5.2. The reliability and validity increase with method triangulation.

In short, service designers have an extensive toolbox with methods for acquiring and organising information. Accessibility to different research methods is essential for the designers to combine the right methods in order to achieve complete, holistic and valid observations. Data mining answers to this eagerness and can supply more and different sources and methods of information. Two characteristics make big data interesting to add to designers toolbox: ‘qualitative vs quantitative’ and ‘human vs machine’.

The qualitative and the quantitative

In the case of service design, the designers gain insights based on the combination of qualitative and quantitative information (Stickdorn et al., 2011). The quantitative resources can guide and prioritise: "what". In contrast, qualitative resources help to answer the reason behind behaviour and symptoms: "why".

The qualitative research is important to service designers because it helps “dig below the outward symptoms of a user experience in order to uncover the motivations that are at its root cause” (Stickdorn et al., 2011, p.166). Although qualitative research supports understanding, explaining and depth, it lacks broadness.

The quantitate insights supports a context where a broader research aids generalisation, direction and validation. Quantitative research is used to prioritise because it can validate how often and how much. However, empathy often lacks from quantitate-only approaches and qualitative research is needed to uncover the causes behind the numbers (Norvaisas & Karpfen, 2014).

The combination of qualitative and quantitative is very powerful because they complement each other. For example, qualitative insights from interviews are validated with quantitative surveys. The other way around, a quantitative, objective and crucial symptom needs to be decoded to the problem.

Designers are challenged to select, combine and adjust different methods to a successful assembly in their daily work. More advanced quantitative methods join the designers' toolbox with data mining. Data science offers new methods, which map underlying human experiences and structures while being relevant and preventing too specific solutions. Data mining will support service designers by revealing more symptoms and validating hypnotises.

Until now, this section showed a classic distinction between qualitative and quantitative approaches. Although big data and data mining are mainly quantitative, some methods in the next chapter demonstrate a more diverse range to what data mining can offer.

Explainable Artificial Intelligence (XAI)

The clarification and communication about decisions and conclusions of AI systems.

Another example is the use of explainable artificial intelligence (XAI). With XAI, it is easier to understand why the system reads something in the data or how factors influence each other because it communicates naturally. The system will explain what symptoms resulted in the conclusion. The diagnose remains a job for the designer.

The human and the machine

Next to additional advanced quantitive techniques, data mining contributes new insights to designers with machine reasoning. Machines perform in a different way, which is an advantage for designers.

First of all, as a machine, it possible to process more and happily perform dull tasks. This means that the design team can make use advantages such as automation, and furthermore have access to more information because of bigger processing capacities. Data mining can assist to convert and highlight specific material from the mass as interesting.

The second contribution of the machine to a human team is a different way of thinking. Computers work with various knowledge representations and have numerous learning techniques. When learning, there is control over the assumptions and fixed concepts, unlike humans. These different ways of learning and thinking will result in alternative conclusions or reasoning can provide a different point of view.

The learning techniques make it also possible to predict or pick up seemingly small signals from the data. Prediction models are already made for design teams (Norvaisas & Karpfen, 2014) and help predict based on application data, user testing data and other sources.

The abilities of data mining compared to humans is not necessarily the opposite. Explainable artificial intelligence (XAI), natural language processing (NLP), image recognition, brain-computer interaction (BCI) and some other fields within AI provide features that approach or exceed human performance. Yet, it is safe to say that, similar to the research methods, machine and human complement each other.

At this point, the challenge is to find the right balance to complement both qualitative & quantitative and human & machine. Therefore I see no reason to assume that the machine will replace the designers. Still, it is reasonable to expect that things might change in the designers daily life.

5.1.2. Complementary expertise

During a project, designers develop extensive knowledge and become a bit more domain expert each time. In this role as expert, the designer can support the data scientist. It is possible to perform data mining without knowing the context of the data[1]. However, domain knowledge is critical extracting meaningful relationships (Xiang et al., 2015). The designer could be a short-cut for the data scientist to expert knowledge.

The designers can share their holistic view, along with translating the real world efficiently. For example, designers can transform an hour interview into a stakeholder network. Another factor that makes designers excellent advisors for data scientists is that service designers are trained to bring value (to the user and/or stakeholders). The challenge of big data is the extraction of meaningful and valuable insights (van der Aalst, 2014b), where the designer can help increase effectiveness and meaning.

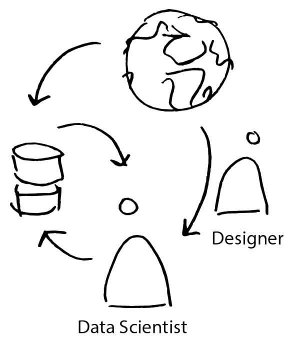


Figure 5.3. The designer as expert

[1] The other way is also possible: preforming data mining without knowing how the technique works. However, in some cases, the analysis relies heavily on data scientists judgment and direct interaction with the data (van der Aalst, 2014a).

5.2. Challenges

The challenges for combining data scientist and designers separates into two main challenges: technical, such as suitable data, and the way of working.

5.2.1. Maturity model

Embedding a new way of working into the organisation might be difficult. Transforming the organisation can be assisted with a maturity model. A maturity model guides and identifies the steps in the process of embedding this new methodology into organisations. Corsten and Prick (2019) defined a service design maturity model. It contains five stages that based on resources, capabilities and organisational structure (Corsten & Prick, 2019).

Figure 5.4. The five stages of the maturity model by Corsten and Prick (2019).

Although the maturity model of Corsten and Prick (2019) applies to service design, it extends to combining data science and design with methodology-independent stages:

Explore This first stage is about trying the new methodology and starting the initiative.

Prove The second stage should create evidence of value and lay the foundations.

Scale Next, the capabilities spread outside the initial team and through the organisation.

Integrate This stage systematically integrates the methodology in the way of working.

Thrive Ultimately, the methodology ingrains into the company culture and pushes the field.

The expanded overview includes transformative identifiers, cues and next steps of these stages in Appendix A1. This section will continue with data science and design specific challenges: technical, value- and capabilities-related difficulties.

Technical challenges

In the early stages *Explore* and *Prove*, some technical data-related challenges arise. Restrictions can originate from the lack of available, quality or access to the data. Data quality expresses not in qualitative content, but about the state of the data. Are duplicates removed, how does empty data look like, is normalisation needed, etc.? The data engineer (role) answers these questions. In case the data belongs to a client, permission might also be a challenge. Getting permission intertwines with other challenges, such as determining the value of the result, the process and cost.

Even though some data is ready for processing, it needs to fit the 'assignment'. Finding the right data to suit the design process is one of the more significant challenges. The needs and specific wishes of the designer change during the project and determining the value and result of the data mining can be complicated, especially if there is no access to data yet. Furthermore, data is not always very flexible. Some data might provide answers at the beginning of the design process, but does not necessarily cover followup questions. This research assists with an overview that demonstrates various matches between the designers' needs and data mining methods.

Determining business value

For increasing the maturity, the evidence of value is essential for most of the stages (Corsten & Prick, 2019). Yet, proving business value might be most difficult in the *Prove* stage. The value will, in this early stage, depend on individual projects. Before starting a data mining project, there are no guarantees for the results. Determining cost will also depend highly on the data source, technique and design context.

Although some predictions expect that the cost of data storage and processor speeds decreases (van der Aalst, 2014a), the cost of data mining depends on several factors. In case the data is clean and processed by a standard tool, the effort is low. However, investment costs increase for a custom-build super-advanced one-time request. In this aspect, data mining is similar to other software tools. The team should approach every project pragmatically. In some cases, only the basic tool with reproducible results are enough.

Capabilities challenge

In the *Scale* stage, the capabilities spread outside the initial team. Applying more and particularly more complex quantitative methods might demand different skills from the design team. Team members will need an essential overlap in the knowledge base for the interpretation of the results for both technically high and low-level data mining projects.

The user researcher might pick up some data science analysis in case that no data science expert is needed. The analyst needs additional knowledge about data science or quantitative research. Expanding the quantitative research speciality might conflict with maintaining depth in other specialities. Subsequently, user research might divide into quantitative and qualitative roles. Teams should also ask themselves who has the responsibility of bringing the quantitative and qualitative insights together

Method triangulation relies on diffuse resources and capabilities, and more and more skills, knowledge and roles are required in project teams. For small teams in particular, it might be problematic to require all the skills while maintaining a budget. Finding a balance between cost and diverse capabilities might be difficult. Norvaisas and Karpfen (2014) describe that big data is used in their User Experience Design Research team at LinkedIn. The team uses, among others A/B testing, analytics and predictive models. They illustrated a few cases where qualitative research was lacking from the quantitative approach. For example, the case of the subscription-based products where quantitative optimisations were surpassed by qualitative-leading redesign (Norvaisas & Karpfen, 2014).

Chapter 6

Data mining methods for service designers

In this research, I examined the data mining supported service design process by developing a guide to concepts of data science methods for service designers. The process consisted of converging, and diverging iterations and is described and reflected in the *Research process* (Chapter 4).

This chapter presents data science methods for service design. The first sections *Overview* (Section 6.1) and *Context* (Section 6.2) provide an introduction and context for the detailed descriptions of the methods. Next, the eleven methods are defined in four categories: *User research* (Section 6.3), *Systems* (Section 6.4), *Serendipity* (Section 6.5) and *Collaboration* (Section 6.6).

6.1. Overview

The methods categorise four groups: 1) user-centred analysing tools (User research), 2) analysing complex systems such as customer journey mapping (Systems), 3) inspiring and insightful generated materials (Serendipity) and 4) joining forces with data scientists in mixed teams (Collaboration):

User research

Some insights are hidden because it is inhuman amount to process, or the signal is too subtle to notice humanely. Data mining could help make more insights available with specialised research tools.

Systems

This group of methods is based on project content and builds, analyses and tests systems. Process mining is, next to data mining, suited for analysing these systems.

Serendipity

Serendipity can help designers in their creative process with exploring relevant materials, generative design and the unique reasoning of machines.

Collaboration

The last category takes a closer look at the collaboration between design and data science. This full-time, part-time or temporary team consists of designers, user researchers and/or data scientists.

6.1.1. Data science capabilities

The eleven methods use data science in different ways and at different levels. This study included both direct and indirect use of data mining. The methods apply data mining by incorporating data science techniques into a tool, by custom build projects or by incorporating data experts. An example of indirect data science into a tool is *Bio translations*, where designers apply a software tool to translate signals from participants.

The required data science capabilities depend on the data science technique and the context. Appendix A5.2 compares the technical levels for the designer and the performer; how easy are the methods to understand, interpret and apply? For example, existing visualising tools are easy to use, while tailor-made *Customer journey mapping* needs professional data scientists.

Because of these different difficulty levels, the methods are recommended for other phases in the *Maturity model* (Section 5.2.1). There are relatively accessible methods in the early phases and methods that require more data and/or team members that appear from the *Scale* phase (Appendix A5.3).

6.1.2. Design process opportunities

The activities of service designers change during the project as modelled in the design process (defined in Section 2.2.1). Designers experience different needs, and data mining offers new ways of providing overview & insights, analysing tools, inspiration and/or collaboration (Appendix A5.4 and A5.2). The methods connect with these different needs and excel at different phases in the design process. Figure 8.1 highlights the most relevant phases of each method.

In particular, some design process phases contain similar goals but require different techniques. For example, the phases *Understand*, *Test*, and *Maintain* benefit from analysing users to gain insights into their characteristics and behaviours. However, the data mining techniques depend on their data, and therefore the subject: test users in a controlled environment or current users in the 'wild'.

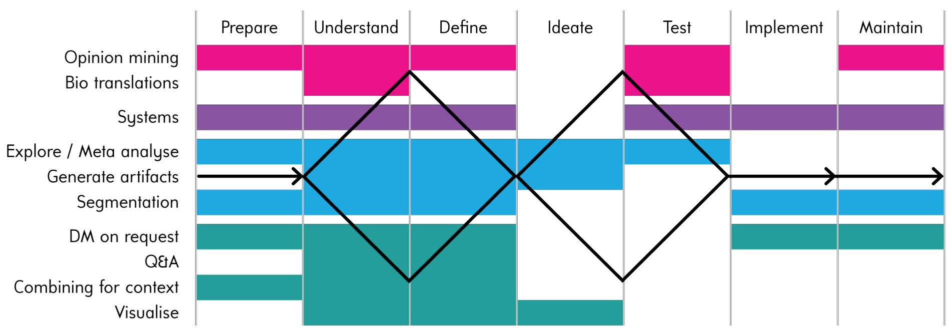
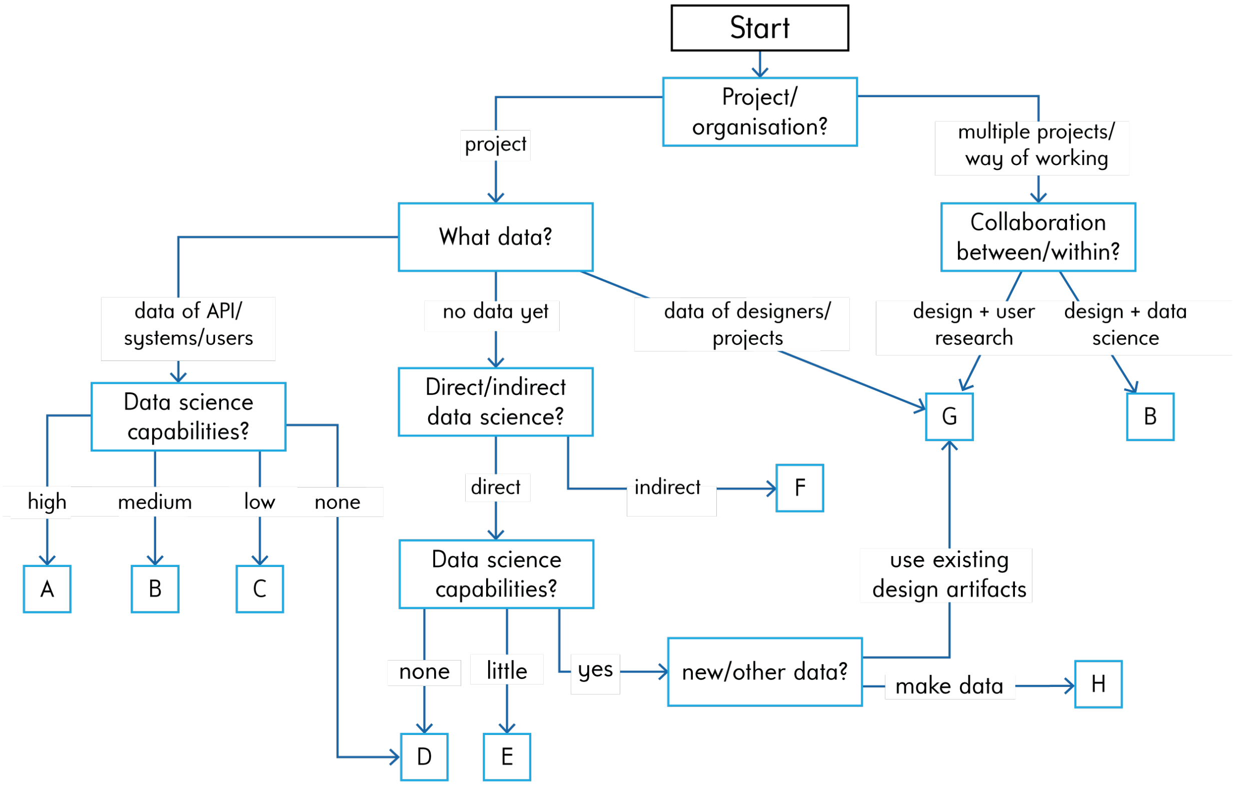


Figure 6.1. Methods in the design process. The most relevant phases of each method are highlighted.

6.1.3. Quick start guide

As mentioned before, selecting a technique or method for a project highly depends on the context. Furthermore, many data mining techniques outside this thesis can also bring value to the designers and/or stakeholders. The following quick start guide might point into the direction of a concept discussed in this chapter.



A With data of systems/users and expertise, you can use *Systems* (Section 6.4) to map a holistic overview.

B Combine the expertise of both design and data science together in *Collaboration* (Section 6.6).

C Use the data to find prominent patterns such as segmentation of users and their behaviours with *Segmentation* (Section 6.5.4).

D Start with quantitative research and learn about experimentation and statistics. Then learn more about the basics to start your first project.

E Use existing open data, such as social media and governmental data. Try and experiment with, for example, *Opinion mining* (Section 6.3.1).

F Data science can be part of (existing) tools to enhance "familiar" user research methods, such as *Bio translations* (Section 6.3.2).

G Collect and analyse generated insights and deliverables for more creativity and/or productivity, as will be explained in *Serendipity* (Section 6.5).

H Use data science expertise to start collecting the required data.

6.2. Context

As described in the *Research process* (Chapter 4), the data science methods for service designers were created to examine how data mining supports the service design process. Therefore, I researched the methods' characteristics, technical feasibility and potential desirability for designers. The upcoming methods sections describe these aspects.

The design critique workshops (described in Section 4.3) were an influential part of the research. Five designers participated in these workshops that evaluated the use of the results of the methods. Due to time constraints, this evaluation included only a selection of the methods. The *Collaboration* and *Systems* categories were excluded because of their collaborative or technical heavy natures.

For workshop evaluations, I developed a fictive case that featured the imaginary company 'Public Transportation Company' (PTC). This hypothetical case provided a practical context. The methods were fictively applied to the PTC case, and visual sketches represented the outcomes (e.g. Figures 4.12 and 6.2). The design critique sections of the upcoming methods sections discuss the results of the design critique workshops.

Furthermore, the PTC case will also illustrate examples in the upcoming methods sections. Example 6.1 introduces the case from the perspective of service designer Olivia.

PTC

Public Transport Company

Example 6.1

PTC

Public transport company, part 1

Hypothetical case

Past year, service designer Olivia has been working on projects in finance and health domain. Today is the kick-off for her new project. The client is PTC, a public transportation company, that operates with long-distance, regional and local transport by train, bus, and in some cities by metro and tram. Various travellers use PTC for various reasons and work, socialise or do daily activities during and around travelling. Olivia and her team are going to develop a new or improved service for PTC.

Her team includes besides designers, a user researcher and data analysist Minji. As a data analysist, Minji can apply existing techniques and interpret the results. If needed, specialists assist or join the team such as data scientist Anne, who is specialised in customised data science algorithms.

6.3. User research

Designers collect information, evidence and insights about the behaviour, feelings and thoughts of people. Some insights are hidden because it is inhuman amount to process, or the signal is too subtle to notice humanely. Data mining could help make more insights available for designers with specialised measuring tools.

These advanced tools that use data mining to extracting more information from users are collected in the *User research* category. This section discusses two methods: *Opinion mining* (Section 6.3.1) analyses large amounts of user-generated text, such as customer feedback, while *Bio translations* (Section 6.3.2) focus on unravelling user emotion and behaviour.

Method

Opinion mining

6.3.1. Opinion mining

Emotions and opinions are enclosed in data, such as conversations, reviews, customer feedback and other consumer-generated content. Designers could request smart processing of this textual data. Data mining can retrieve frequent patterns or relations between subjects, opinions and emotion. Opinion mining, also called sentiment analysis, is a subfield of data mining and focusses on extracting and analysing opinions (Balazs & Velásquez, 2016; Poria, Cambria, & Gelbukh, 2016). It will help the designers to orientate what sentiments in what degree play a role in the experience of the users (Example 6.2). The correlations can help point in the right direction what the cause is of their sentiment or opinion.

Example 6.2

PTC

Public transport company, part 2

Hypothetical case

In the hypothetical case of PTC, designer Olivia works together with data analysist Minji. Minji collected the tweets of the past year that mention (travelling by) train and an activity from the list that Olivia supplied. The tweets are grouped per activity and measured if the tweet was positive or negative. Minji and Olivia discuss the results. Apparently, tweets about 'working' and 'eating' in the train were mostly positive, while other activities such as 'chatting' were negative. Olivia looks at an example tweet for 'eating': "The chocolate and hazelnut croissant from @pret was such a messy but delightful breakfast! i'm glad no one was sat next to me on the train! soo good!" (Gregory, 2019).

Later, when the team decided to dive deeper into the food consumption habit, Olivia asks Minji if she can find out when people are likely to eat on the train. Minji plots the timestamps of the train+eat related tweets in a histogram, and they notice that both lunch and breakfast are popular. Next, they plot the same data over the year; it becomes visible that lunch has a relatively steady curve, and breakfast was trending.

Olivia and her team used this information together with other user research for inspiration and prioritising. In the end, the team delivered a concept called 'eating compartment' which is related to the silence compartment but brings people together for shameless consuming breakfast, lunch or dinner.

Overview

One of the more straightforward opinion mining techniques is classification. Polarity classification (Jin, Ho, & Srihari, 2009) identifies opinions as a positive or negative sentiment. Besides polarity, classification of other emotional states is also possible (Balazs & Velásquez, 2016). For example, Neviarouskaya, Prendinger, and Ishizuka (2010) classified various emotions, such as anger, fear, joy and interest, from informal online conversations.

When the sentiment is identified, further analysis can detect the subject (called aspect) and if the sentiment is general or aspect-specific. More beneficial, the aspect-specific opinion (clear, blurry, etc.) is context dependable and provides a reason for the sentiment (Xiong, Meng, Shen, & Yin, 2017).

Additional and in-depth analysis is possible when beside text also ratings are available. Then data mining can extract the factors that correlate to their experience. Xiang et al. (2015) applied the technique factor analysis on Expedia.com reviews and determined what factors and experience-related words correlate in which degree with the experience rating and what the relations are between factors. For instance, "A guest who stays with family members seems to be not interested in the service aspect of the hotel other than a spacious room and attractions nearby." (Xiang et al., 2015, p. 128).

Factor analysis

A statistical method that finds correlations with observed variables and unobserved variables called factors.

Considerations

It is important to understand the impact of the data source, which is consumer-generated content. Biases in producing (and reading) reviews should be kept in mind, such as the self-selection bias (Li & Hitt, 2008) and participation bias. The sentiment in the data could also be biased, such as the positive hotel customer satisfaction rating (Xiang et al., 2015) or negative customer feedback.

Design critique

In the workshops (Section 6.2) the designers discussed three versions of *Opinion mining*: words with emotion scores and associations (Appendix A7), relations between factors (Figure 6.2) and a word-cloud variation (Appendix A7). Both the word-cloud and association versions did not appeal to the designers. The visualisations lacked inspiration and offered no context. However, the relations version was a favourite and inspired the designers to develop the version further.

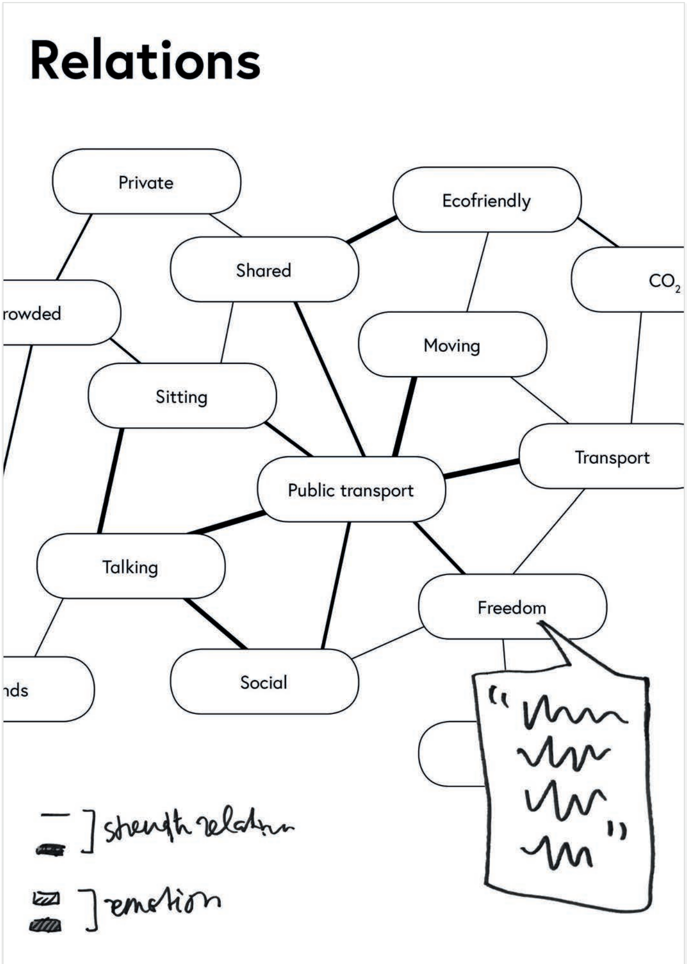


Figure 6.2. A visual representation of the fictive mined word relations for the PTC case. Alterations were made during a workshop to show more about the relationship and the words.

The designers all said similar things about the relations extracted with opinion mining. They appreciated that the relations have explanatory value and that the visualisation showed the strength of a relation. Both Designer K and Designer F suggested the use of colour to indicate positive or negative sentiment.

The context and explanation of the relationship were crucial and clicking on it should show details and examples. Then the designers have enough context to determine nuance, continue researching, and as Designer A stated: “create empathy”. Designer F explained that further investigation is still needed because people do not always say what they want or know what they need. On the other hand, reviews can provoke more honest and extreme opinions than interviewing, according to Designer K. Additionally, Designer A would like to connect the relations to touchpoints in a journey.

The designers provided a wide range of use-case examples of the interactive network from creative to informational. It could be used as starting-point, for inspiration, in addition to own mind-map/brainstorm or addition/replacement of interviews. "Reviews provide insights when no time to interview a diverse range of people. Now you can do more people at the same time" said Designer K.

Conclusion

Opinion mining makes use of consumer-generated content such as social media, reviews and customer feedback. This required input is relatively easy to obtain but might contain some biases. With opinion mining, different setups are feasible to a) detect the frequency of factors, positive/negative sentiment, b) classify defined emotions or c) find correlations between factors and experience.

The method informs the designer about the users' satisfaction, problems, frustrations and celebrations. The advantages compared to interviews and surveys is that no explicit participants are needed and the opinion given in a non-experimental setting.

During the design critique, the designers valued the method but proved that the communication about the results could improve. The designers need context and nuance of the sentiment values and correlations. The visualisation benefits from an interactive element to show details and/or examples. Another way to provide context is by involving the designers in the mining process.

Method

Bio translations

6.3.2. Bio translations

Human emotions, feelings could be deduced from data using biological and psychological principles. It could be used to process more at the same time (e.g. user tests) or detect seemingly unmeasurable small signals. With these techniques, the machine can interpreter emotions and behaviours for testing and comparing scenarios/prototypes or measuring key performance indicators (kpi's). Furthermore, these techniques are useful to highlight parts of recorded material and leave the interpretation to the designer. The machine is in that case trained to select specific sections for the designer to review.

Labelled data

Data where the data-points have tags called labels, which can be seen as the correct answers.

In contrast to most analysing and clustering data techniques, *Bio translations* decodes signals with a trained model. The techniques first learn from a labelled training dataset - observed signals of users. When training is complete, the condition of a new individual could be predicted correctly, even in a new situation. Data sources suitable to extract emotions are video, voice or audio, smart devices or electroencephalography (EEG). Other data sources are computer logs, screen activities, eye tracking, motion capture (for location and posture) and locating systems (Zheng et al., 2015)

Example 6.3

Braingineers

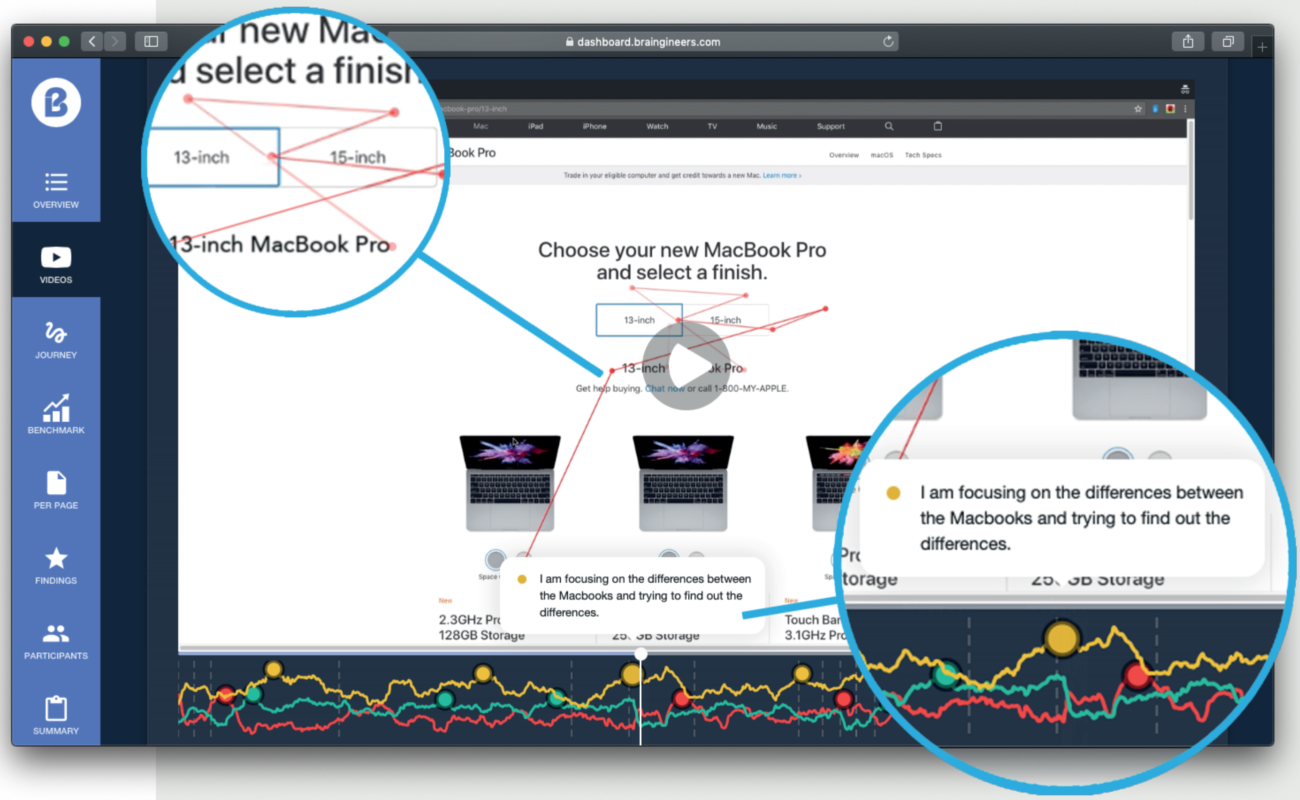
Demonstration with the Apple, product purchase flow

Conducted before 2018

Braingineers tracks emotions during a user test of a digital customer journey. The participant performs a task in a controlled environment while a wireless 14-channel EEG headset collects EEG signals. Next, the system interprets these signals into joy, attention and frustration levels (Braingineers, n.d.-d). The system learned noise-cancelling and interpretation of the EEG by a neural network technique (deep learning) (Braingineers, n.d.-c). These levels are tracked over time, together with a video of the computer screen, eye and mouse tracking. The system selects specific moments, which the participant and the researcher discuss after performing the task. This manually added feedback and they collect the emotion tracks from multiple participants.

An interactive dashboard application presents the user test results. One of the demos on the dashboards shows the analysis of the apple product flow (available at `dashboard.braingineers.com`[a]). The dashboard ends with a "consultant summary", which is likely based on human conclusions based on the analysis. In the demo, they concluded that looking at the visuals of the product overview and detail page increases joy (Braingineers, n.d.-a, p1).

[a] The complete url is dashboard.braingineers.com/dashboard/campaign/demo-apple-product-purchase-flow/



Braingineers dashboard with apple demo (Braingineers, n.d.-b).

Overview

The *Bio translations* methods split into two kinds: emotions interpreters, such as Braingineers that uses EEG signals (Example 6.3), and behaviours identifiers. For capturing and coding behaviour are cameras, smart devices, eye tracking and other recording methods a valid data source.

For example, Weibel et al. (2013) used multiple Microsoft Kinects (3D cameras) to analyse physician-patient communications. After recording, they coded various behaviours, such as physical actions and speech interactions (but no transcriptions). The output is visible in Figure 6.3. Weibel et al. (2013) found communication patterns and additional usage patterns for their application (medical documentation system).

Weibel et al. (2013) performed the coding and analysis manually, which took approximately 150 hours. Many coding and patterns recognition are relatively easy tasks for data mining, which could have allowed them to make the same conclusions quicker with automated processes.

Figure 6.3. ChronoViz shows videos of Kinects and timelines with annotations of speakers, their body positions, and what they are interacting with (Weibel et al., 2013).

Considerations

When recording for *Bio translations* in the real world or a controlled environment, the amount of noise influences the results of classifying situations or interpreted behaviour and emotions. Controlling the noise is especially important when the signal in the data is small; such is the case with EEG data. If needed, solutions are a) prevent noise, b) have consistent noise and c) use noise detection and reduction techniques.

Another consideration is the level of intrusiveness when selecting an ethnographic recording method. For instance, audio recordings are less intrusive as electrodes connected to the skull. It is even possible to track items, such as clothing or books, instead of users (Zhou, Shangguan, Zheng, Yang, & Liu, 2017). In that case, Zhou et al. (2017) used passive RFID tags and classification models to detect customer actions, for example, pay attention to, pick out and turn over. This way, they detected how customers browse stores.

Design critique (Video Analyses)

In the workshops (Section 6.2), *Bio translations* was tested as with two data sources 1) Video and 2) GPS. The video analysis cards for the workshops contained several types: video of a single journey (Figure 6.4a), interview (Appendix A7) and user test (Appendix A7), as well as the analysis of multiple journeys (Figure 6.4b). The system provides two functionalities: easy rewatching of the recording by smart highlights and an analysis of the emotions of the user.

The video of a single journey, called ‘Marcel’s journey’, got much positive attention from the designers. The single journey was Marcel who wore a camera during an activity. The system tracks his emotions over time and highlights certain periods. The single journey was “super super personal” according to

Designer J. All designers stated the potential of uninterrupted shadowing from the point of the user and interviewing the user afterwards. It becomes more efficient, said Designer K.

The designers likewise appreciated the analysis functionality for multiple journeys and user testing, but not for analysing a single journey.

The single journey analysis specifically was not embraced by Designer J, who strongly preferred doing all research personally. The designer accepts the additional input of others (machine or human) when confronted with the positive contribution of a different point of view. However, Designer J keeps watching all recorded material even when it exceeds a reasonable amount of hours. The designer would even rewatch complete interviews conducted by others.

In contrast, the analysis of the other versions was popular. The multiple journeys analysis would be "time-efficient" to use it in a customer journey map said Designer K, who imagined a customisable copy-paste functionality for the graph with the average experience. Designer J would use it to detect similarities between users and test a broader group.

Designer J and Designer D also praised the analysis part of the user test. This analysis is the same as Marcel's journey only is a user test recorded. The analysis registers more emotion during the interaction than currently thinks Designer D. Designer K would only do live user test and personally analyse, but notes that "much data might be useful".

Design critique (GPS tracking)

During the workshops, we tested the second data source, GPS tracking, in two versions: with and without heart-rate (Appendix A7). The designers made it clear that only GPS data was not enough. "So? People walk. What does this tell me?" questioned Designer F. The heart-rate data improves the map a little, but still lacks interpretation.

The tracking would improve with an abstract layer of behaviours and/or mental states, suggested Designer K. Certain areas could be highlighted to indicate that something is happening. The designer then further investigates this area. Designer A plans to translate the heart-rate to 'elevated' states, such as stress and happiness. Furthermore, could other information (e.g. from an app), help to understand the intent and situation of the user better.

Conclusion

Bio translations allow for more advanced user measuring tools. The techniques use examples to interpret emotions, aid in the identification of behaviours, compare situations and highlight relevant parts. A range of data sources is suited to extract emotions or classify behaviour with various levels of intrusiveness. Another factor to consider when recording data is the amount of noise in the environment or sensors.

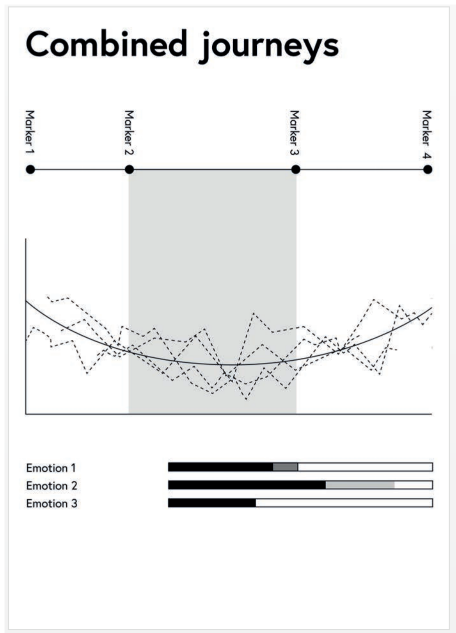
This method makes it possible to measure new inner states of users (e.g.

extract emotions) or process more recordings (classify and highlight data). It will enable the designer to understand the journey of customers and measure quantitative emotions. Especially less intrusive recording methods will provide insight into the unconscious behaviours, similar to observations. Furthermore, the observations by designers can be enhanced by the objective inner state analysis of *Bio translations*.

The type of video (journey, interview or test) clearly influences the purpose of the tools. The designers highly valued especially the quantification of the journeys/tests and analyse of user tests in the design critique. *Bio translations* by tracking with GPS and smart devices should also focus on abstract layers with mental states, behaviours or emotions and context. Bare tracking lacked empathy with the users.

Various interpreter tools exist or could be developed to support designers. These tools should keep an eye out for the two main features of *Bio translations* (measure mental affairs and speedy recordings processing) and selected their data and recording devices accordantly.

(a) 'Marcel's journey' is an analysed video, with emotions tracked and time periods highlighted. Photo by Nylind (2014).



(b) Journeys of multiple users are combined in a graph with markers placed in time for identifying events.

Figure 6.4. Fictive video analyses for the PTC case.

6.4. Systems

This group of methods is based on project content and builds, analyses and tests systems. Next to data mining, process mining is suited for analysing these systems. Process mining aims to use event data to extract process-related information, such as automatically building a process model by observing events (van der Aalst, 2011).

Designers encounter these systems in their work as structures, infrastructure and processes (Yu & Sangiorgi, 2014). Artifact examples are stakeholder maps, *Customer journey mapping* (Section 6.4.1) and service blueprints, but also insights into the processes of applications and other systems are useful. The data can translate into valuable insights related to process performance and compliance (van der Aalst, 2014b). Data mining or process mining can help understand and design these systems. The full scale of mining for systems is broad, but parts can be applied independently.

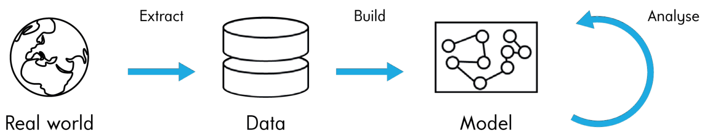


Figure 6.5. Basic steps in for building and analysing the model of a system.

The process is as follows: first, data generates a model that represents the actual, expected or desired system. The model could be used to analyse, predict, compare, discover, monitor, improve and test (Bernard & Andritsos, 2017b). The analysis can match a specific problem (e.g. bottleneck analysis) or provide insight into an overall picture of the situation(s). Another possibility is adjusting and retesting the model as a prototype.

The flexibility of these methods suits the service designers process. The model could represent the current and imaginary situations. Implementation could extend a small proof of concept and is thus suitable for agile development. The overview and insights are useful for complex situations involving complicated processes or actors. In order to apply process mining, the event logs and/or data must be available. Data requires the presence of digital processes or digital evidence. If such data is not available, the team could invest in a digital trace of the service. This trace is useful for performance measurements, even is the complexity is low. With transparent or straightforward systems, investment in this group of methods is less suitable.

At the other end of the complexity-spectrum is the digital twin. Digital twins are virtual duplicates of super-complex systems, such as aerospace manufacturing. The real-world links interchangeably the twin: the changes in the physical or designed system are automatically tested and implemented in the other (Tao et al., 2018).

Example 6.4

PTC

Public transport company, part 3

Hypothetical case

For PTC, the transportation system itself is an immense complex logistic system. Problems in logistics may occur when the actual and planned schedule diverge too much. The applications for planning or monitoring traffic and resources are fragmented and isolated. Data scientist Anne works with a small team to build a *de facto* model from the logs of these applications. This model reflects not the planned but the actual processes.

The model detects several problem areas because these situations deviate strongly from the planned situations. Service designer Olivia assists in prioritising the results. The selected problem area influences the customer experience: seemingly irregular delays in the maintenance of the passenger trains cause considerable delays later (more than 10 minutes).

The design team focuses on this issue that conductors sometimes do not have enough time for inspections, and it is unclear if or why the planning systematically falls short. Olivia and Anne dive deeper into the case. Based on experience and domain knowledge, Olivia proposes factors that might play a key in the seemingly irregular delays. Then, Anne uses the models to validate these ideas. As a result, they discover that the planning did not match with the actual time spend when inspecting in a specific type of vehicles.

Olivia continues the research by shadowing a conductor on two types of vehicles (delay and control group). It becomes clear that the accessibility in that type of vehicle is low. On the short term, the planning algorithm is adjusted to have more time on these vehicles, while the design team investigates the best solution for the inspecting conductors.

Method

Customer journey mapping

6.4.1. Customer journey mapping

Organisations benefit from optimising the customer journey (van der Aalst, 2014a). Besides event logs are websites, (after) sales, support and social media suitable for extraction, mapping and analyse of the customer journey (van der Aalst, 2014a). With the customer journey map (CJM) is the customer journey mapped to represent a journey. The represented journey can be one or a combination of actual, expected or desired journeys. Følstad, Kvale, and Halvorsrud (2013) describe the difference between the *expected* (“theoretical”) and *actual* (“experienced”) journey.

Overview

The CJM framework of Bernard and Andritsos (2017b) embeds process mining into the expected and actual journey mapping. They defined the *de jure* model that represents the expected system and the *de facto* model that describes the real world. The models, combined or alone, offer several tools: explore, predict, compare, enhance and diagnose (Bernard & Andritsos, 2017b). Figure 6.6 shows an overview of these processes.

With process mining, the *de facto* model is extracted from the collected data (event logs), and it provides insights to the current situation of the customers (Harbich, Bernard, Berkes, Garbinato, & Andritsos, 2017). This actual journey map represents the "real" experience and should be based on the facts, contrary to the expected journey map that is useful for strategies or ideation (Bernard & Andritsos, 2017b). Comparing the real journey to the *de jure* model demonstrates the differences between the applied and planned journey. The service can be adjusted to match the expected journey, or the designed journey can be improved.

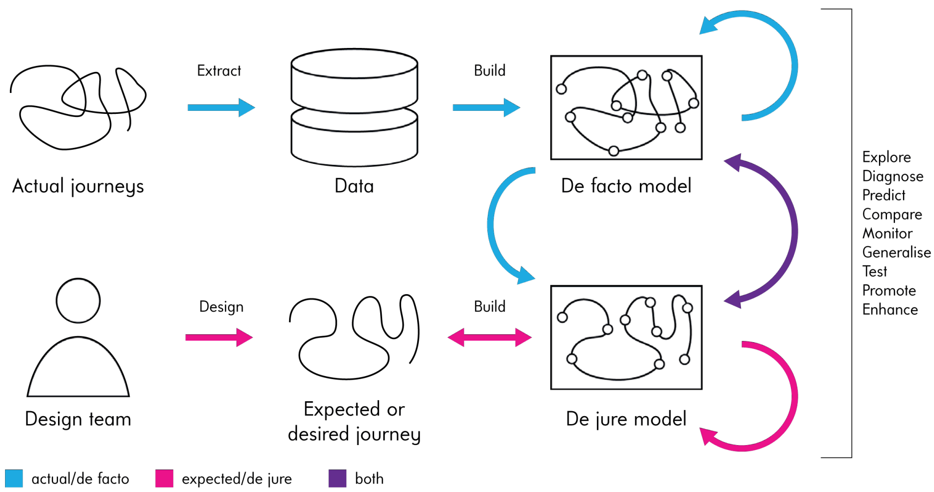


Figure 6.6. Overview of the relations between the actual, expected and desired customer journeys with their models.

Examples of similar CJM are the 'mixed' extraction of Halvorsrud et al. (2016) and predictive modelling of Harbich et al. (2017).

Halvorsrud et al. (2016) used a visual representation of the expected and actual customer journey. The combination of diary studies and backend logs reconstructed the broadband onboarding journeys. The couple proved powerful because participants are inaccurate and logs have difficulties with ad-hoc touchpoints.

Harbich et al. (2017) extracted individual journeys from event logs to detect the journeys of users (Figure 6.7). They used Markov models with data from the daily activities of Chicago citizens and concluded that it was possible to find not only most likely journey but also alternatives/divergent journeys. These alternatives are "useful for investigating how a journey might deviate from the most likely representative journey" (Harbich et al., 2017, p. 6). Their model could predict the

Markov model

Model that represents states and predicts the (best) next state based on partially or fully observable systems.

Probabilistic model

Model that produces a probability distribution as a solution. Antonym of Deterministic model.

most probable event of an incomplete journey and predict likely future journeys.
Hierarchical clustering algorithms are also used for grouping underlaying journeys (Bernard & Andritsos, 2017a), and depending on the project, a deterministic or probabilistic algorithm can be selected.

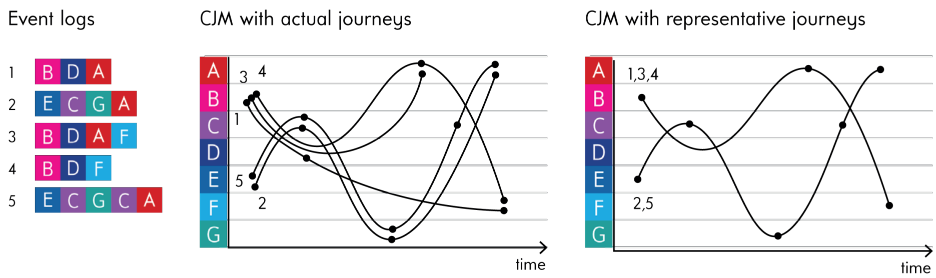


Figure 6.7. Harbich et al. CJM extraction (2017). 1) The event log contains five journeys, where each letter represents an activity type. 2) The individual journeys are mapped and 3) two common journeys found.

Considerations

The quality of the customer journey map depends highly on the available data. There must be enough data, and it must contain the details that are relevant for the journey. Besides factual touchpoints, the team can enrich the journey map with *Opinion mining* or other empirical tools to contain the complexity of the customers' needs (Bernard & Andritsos, 2017b). Therefore, applying this method might be less suited for less complicated projects.

Conclusion

Service designers work with complex systems such as customer journeys and the processes of applications and/or services. *Systems* can assist in extracting models from the real world with event logs and other sources. The models can represent the actual, expected or designs system to explore, predict, monitor, compare, enhance and diagnose. If the system is complicated enough, investing in building models results in an extensive and enduring tool that reminds of a digital twin.

Especially *Customer journey mapping* is an interesting *Systems* method that produces insights about individual, divergent and common journeys. Furthermore, these models are useful to close the 'gap' to the expected/designed journey. Similar to other methods that are discussed in this thesis, might an additional layer of emotions, experiences and other inner states interpretations contribute to the value compared with an emotionless representation.

6.5. Serendipity

Serendipity can help designers in their creative process. Exploring could provide insight into the material but could also spark a new idea when encountering the unexpected. Generative design, design made by machines, could also surprise and provoke a reaction. The reasoning of machines can provide a different point of view.

The definition of serendipity is discovering pertinent information or something of value, either without intentionally seeking or when looking for something else (Agarwal, 2015; de Melo, 2018; Friedel, 2001). It is also possible to look for something, where the discovery itself was an "accident" (Friedel, 2001).

These discoveries lead to innovation, but also creativity: "Serendipity is intrinsically related to ideation" (de Melo, 2018, p. 49). de Melo (2018) summarises that serendipity can spark a change in the course of action, interpretation and perception of the overall picture. These moments, where insights fall on the right place, are elementary for the creative process (de Melo, 2018).

Serendipity could be stimulated by scouting the materials produced by designers in *Explore Tools, Artifacts and Insights* (Section 6.5.1) or analysing designers and their materials in *Meta analyse* (Section 6.5.2). This chapter will focus on the tools, artifacts and insights (TAI) involved in the design process and projects. Section 6.5.1 explains more about TAI.

Generating artifacts (Section 6.5.3) also stimulates inspiration and insights. An example are personas which combine and complement knowledge about the users. Revealing insights and defying predefined structures is part of *Segmentation* (Section 6.5.4).

TAI

Tools, artifacts and insights made by/for (service) designers.

The *Serendipity* category contains the following four methods:

Based on collection of TAI

Explore Tools, Artifacts and Insights
Data mining helps designers find what they need by extracting and relating all sort of materials. An application with these techniques can present relevant items and automatically label information.

Meta analyse
Patterns in the materials of designers reveal how their work and prevent reinventing the wheel. Furthermore, data mining can analyse insights for higher level and cross-domain knowledge.

Based on artifacts or instances

Generating artifacts
With data mining, specific knowledge could be prepared in artefacts or show an alternative version. Machine generation delivers inspiration or automated tools, such as autocomplete functions.

Segmentation
Segmentation provides more, easier or alternative insights about the target. The value of alternative segmentation is not only what the segments are, but mostly why these groups are made that way.

Method

Explore TAI

6.5.1. Explore Tools, Artifacts and Insights

Designers inspire and learn from each other. Data mining can help to find what the designer needs by extracting and relating all sort of materials. From a vast collection of materials is a subset of relevant items presented. Exploring tools, artifacts and insights (TAI) might a) inspire, b) prevent designer's equivalent of a 'writer's block', c) inform when switching between domains or projects and d) keeping an eye out for what colleagues are doing.

An application for exploring will benefit from data mining because data science techniques can detect what is relevant (better explore/search results), automatically label information and make data available for *Meta analyse* (Section 6.5.2).

Example 6.5

PTC

Public transport company, part 4

Hypothetical case

Service designer Luciana joins the PTC project that is ongoing. She wants to contribute to the user research but does not want to redo the work of her teammates. Luciana uses the 'experience explorer', an application that collects research, project and client insights. Designers and user researchers make their (intermediate) results available through this application for colleagues and stakeholders. It can show research results and derived knowledge together with their context (what and how).

In the 'explorer', Luciana looks at the automatically generated summary of PTC, which teammate Olivia shared. For some insights, she reads the detail page, which tells her how this information was acquired.

She feels updated about the project and continues searching for other related insights in the 'experience explorer'. Even she selects the domain "traffic", the amount of results is enormous. Luckily, the application orders the results with a smart algorithm. It uses clickstreams of users and an internal network of relations to predict the relevance. Luciana wanders in the information of explorer until she reads an interesting page about a research method that was useful in another project.

Luciana discusses the method with the team and decides to use it. After the fruitful execution, teammate Minji helps Luciana adding the results to the 'explorer'. Adding the labels is automated, but she can update them. Furthermore, linking the results to the project and the existing method was just a couple of clicks. She shares the results in more detail with the team. The application also shares the method with co-workers on the "what is going on" page.

As a result, Luciana is up-to-date with the team, selected a successful method, and the application increased the relevance of the used items.

Overview

The TAI are explorable with an interactive system which provides personalised and relevant suggestions. Optionally, some random or most-views items expand the presented items. It might induce serendipity as a 'System for Serendipity' where the medium helps to make surprising discoveries (de Melo, 2012). Other features (e.g. filtering and search) and traits (e.g. immediateness and playfulness) as defined by de Melo (2012) could enhance the exploring TAI system.

With data-driven design, user research plays a significant role. The explorative application can support preventing information loss in such a design process and be independent of individuals. Data science can aid in finding the relevant resources and analyse the content for higher level and cross-domain insights (*Meta analyse* Section 6.5.2).

Costa et al. (2018) describe software (e.g. Nvivo, Atlas) that is used for (qualitative) research and includes, among others, text information, interview transcripts, audio and images. These systems can aid in recording, sorting, matching and linking of research insights (Costa et al., 2018).

Designers can use a variety of materials for exploring, from the design community to a specific project. The following examples are not equally valuable for designers, yet possible:

Core design materials	**Design community materials**
e.g. deliverables, notes, insights, user research results, artifacts, other material of/for clients	e.g. conferences materials, blogs, portfolios, tools, paper cards decks, other non-client materials

Considerations

The primary function of the exploring system is informing the designer with relevant information, but it might also be useful for inspiration or serendipity. This last feature of the system might be difficult since inspiration, creativity and serendipity can not be forced, as the mind and mental capacity plays a part (de Melo, 2012, 2018; Friedel, 2001). The system should create the right environment for creativity while fitting the design process. It will be a challenge since systems based on our habits and behaviour, do not truly surprise us (de Melo, 2018).

More importantly, the implementation of the system profoundly influences the practical use. 'Relevance' and 'novelty' might be prominent characteristics of the system. Data mining can help with recommendations and analysis. The experience probably influences its value considerably. Is there enough (new) material to keep interesting? Can you share information? How do the teams collaborate?

Similar as will be discussed in *Meta analyse* (Section 6.5.2), the amount and type of data collected also influence the performance.

Design critique

How designers make and handle insights became evident in the workshops (Section 6.2). We discussed three versions of an exploring system: projects (Figure 6.8a), methods[1] (Appendix A7) and insights (Figure 6.8b). The versions contained similar information from a different perspective. For example, the project version shows related projects, and this detailed view presents information about the client, project, methods used and insights.

The methods version was less interesting for the designers. Picking and adjusting methods themselves showed important to the designers. Designer K explained: "For inspiration it's ok, but a match is really hard to find. Because I make my own methods".

The designers debated the most about insights explorer. All designers agree that developing insights is part of the design process and objectivity is essential because subjectivity influences the insights from the user research. The methods and insights versions lack this objectivity according to Designer K. The subjectivity bothers Designer J too: "he/she has already put some kind of point of view on it. So I would never trust 100% the outcome". Designer D acknowledges the subjectivity but places it in perspective: "Everything what you find is also biased. ... Even though it might be coloured, you decide what you wanna do with it". Additionally, Designer J has more reasons to keep performing user research: "It is something I really enjoy".

For applying, two clear situations arise in the workshops. The insights are useful when switching to a new project or when there is no time to do the research. The 'onboarding package' is positively received by all designers as "extremely useful". Designer D promotes the insights explorer and states that starting with the insights is "a more useful tool then specific projects" because it provides a broader view. Designer K turns it around and suggests placing the insights under a project to create context, such as the project version explorer does. As a result, Designer K and Designer J prefered the project explorer.

Onboarding package

Collection of information for kickstarting or onboarding a project.

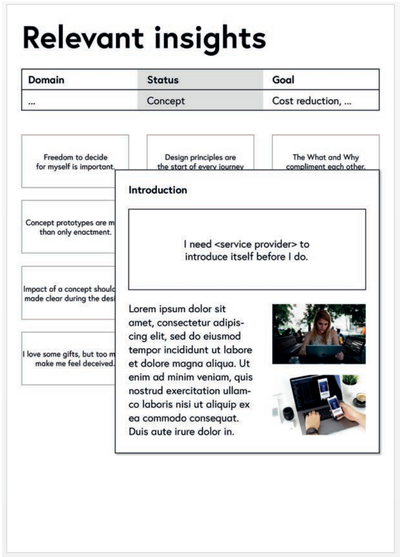
The project explorer was the most popular starting point for most designers. They perceived this version as less subjective than the other versions. Designer J, who was very sceptical about the insights, would "definitely" use the project version for inspiration and background information. The designer tells about time constraints for user research. "You start, and you are 100% completely focused on your client, topic. Sometimes you forget to open your eyes and look outside and look to what other people are doing". Related projects would help Designer J to break out of the narrow scope of the sprint. The designer would like to do more related projects and "this method would be a quicker way to access more."

Sprint

A time-boxed SCRUM iteration where activities defined at the start.

[1] Related to artifacts.

(a) The related projects explorer where a competitor is selected in the domain 'transport'.



(b) The insights explorer shows a similar layout with different content.

Figure 6.8. Fictive TAI exploration application. Photos from `unsplash.com`.

Conclusion

Exploring and finding the right TAI can help the designer with relevant information and new inspiration. It enables the designer to kickstart the project with existing information and combine knowledge for new ideas. Data mining can help to analyse and improve exploring by predicting what relevant is for the designer.

When the user research team and the design team are collaborating, might the exploring system aid and limit the information loss. Two other use scenarios from the evaluation workshop are the onboarding package when a designer enters a new project and as compensation for tight budget analysing phases.

Creating the explorer will require some research about what and how the designer wants to find information. A variety of materials could be used, but are not equally valuable for designers. For example, during the design critique, the designers disapproved of the method explorer because they prefer to make their methods. Collecting tools and artifacts are therefore less useful.

The UX of the explorer system is also essential and should guarantee the relevance, novelty and objectivity of information. The reliability of the information was an evident concern in the design critique. The creator and the method influence the information; therefore, the source and context should be transparent.

Method

Meta analyse

6.5.2. Meta analyse

Data mining can help understand what designers research and make by revealing patterns in their tools, artifacts and insights (TAI). Patterns in the materials help prevent reinventing the wheel. The analytics are useful for optimising the design process. Moreover, the techniques can analyse for new insights about tools or users. Data mining can analyse insights for higher level and cross-domain knowledge.

Considerations

The amount and type (e.g. which of TAI) of data collected for analysing will determine the results significantly. Processed information, such as tools, will have a different result as detailed materials as insights. Although insights have more potential to uncover novelties, the risk of not finding desired results is also higher. For example, if results need to generalise over projects, then enough projects that participate are needed. Collecting and sharing results might be sensitive for clients and security rules might be in order, such as using the data only internally.

Insight

Understanding from observation, information or other design/user research.

Another consideration is how the designers will use the results. When and how will the designers use the analyse in their daily work? The design critique of exploring TAI showed that the designers prefer to find their own way. Many design card decks, checklists, handbooks, posters, kits, bookmarks, fundamentals, laws and other collections exist however[2]. Further research could show how teams handle these resources, if insights and summarises made by machines contribute. The 'onboarding package' or explorer discussed in *Explore Tools, Artifacts and Insights* (Section 6.5.1) might be one of the possibilities to use *Meta analyse* on TAI.

Conclusion

The value of analysing design on a meta-level depends on the the type of analysed data. Analysing user insights be particularly interesting compared with the other TAI. Tools and artifacts result in more an efficient design process, but analysing user research can find trends and general insights about users. Understanding the user appeared in the design critique of exploring TAI method more desirable that informing about tools and artifacts.

How the designers use the newly mined insights in the design process, need more refinement. Integrating with the 'onboarding package' and explorer of *Explore Tools, Artifacts and Insights* (Section 6.5.1) might be a possibility to use *Meta analyse* on TAI.

2 For example: https://www.checklist.design/, https://ukhomeoffice.github.io/accessibility-posters/, https://lawsofux.com/, https://www.evernote.design/, https://resourcecards.com, http://typographyhandbook.com and http://designresources.party/

6.5.3. Generating artifacts

Method

Generating artifacts

The intention of generating artifacts by machine is not to replace designing but merely to provide tools or an alternative view on things. With data mining, generated artifacts can prepare certain knowledge or show and explain an alternative version. Machines can these generate artifacts by learning from examples of other projects. Combining with other sources, such as social media, contributes to enriched results.

Machine generation can aid designers next to an alternative perspective with quicker (user) testing. By learning from examples, prototypes can be made quicker and supplement (trivial) parts of the prototype. Machine testing should not replace user testing, but machine-generated user test results can aid for additional quick and dirty testing.

Generated artifacts and representations of services that are closer to service designers could deliver inspiration or automated tools. Although other design-related products could be generated, this thesis will focus on personas (this section) and *Segmentation* (Section 6.5.4).

Example 6.6

PTC

Public transport company, part 5

Hypothetical case

For the PTC case, service designer Olivia organised a co-create session with the stakeholders. In the first part of the session, the participants were divided into two separate groups. Each group imagined being a user and designed a scenario where the mobile phone could play a role. The participants make sketches on paper, test them and play with the scenario.

During the coffee break, Olivia uses the sketches to autogenerate prototypes. In the second part, she asks if the groups would like to play the scenario with the prototype of the other group. The group watch their scenario being played and see some struggles they not anticipated. The next group takes its turn after a small evaluation round. In the end, the co-create session closes with a moment of feedback and final comments.

The prototype showed a more honest use-case than the paper version because it required fewer introductions and interference for the test user. At the same time, stakeholders enjoyed the fact that their sketches “became alive” and learned a lot from co-creating and the user test.

Overview

Generative design can be inspiring and computational (visual) art is a clear illustration of the possibilities. For example, machine learning can be trained on existing paintings to generate paintings such as Elgammal, Liu, Elhoseiny, and Mazzone did with their Generative Adversarial Networks (GAN) (2017).

The algorithms can be designed to produce more refined or structured results. For instance, Karras, Laine, and Aila used GAN to generate faces by selecting two

Generative adversarial networks (GAN)

Artificial neural networks are trained to respectively generate and evaluate new data based on the original data.

faces, and they were able to choose coarse, middle and fine style ratios (2019) (Figure 6.10). Alternatively, patterns can be extracted from other sources and could also generate new things. For example, the Perception Engines of White (2018) learns from the photos of real objects (Figure 6.9).

Figure 6.9. Flat Fan of a Perception Engines by White (2018)

Design system

Collection of design elements and standards for guiding and embodiment of the brand.

Visual saliency

Subjective quality of visual perceived items and if they grab the attention.

Another way for data mining to support with generating is in the form of automation tools. Existing design methods such as sketching could be enhanced by automated code generation (Siering, 2017; Wilkins, n.d.) or produce code based on designs (Beltramelli, 2018). One existing online tool is `https://uizard.io/`. Coded versions of priority guides, wireframes and other frameworks could be helpful when prototyping or designing and soon combined with a design system.

Next to content or design can feedback from users be generated. For testing designs and services, real users should be a priority. However, more and faster testing can be available by generating test results, which is useful when projects are low budget and/or quick extra testing is desirable. An example is the predicted visual saliency map (Cornia, Baraldi, Serra, & Cucchiara, 2018).

Based on a photo, a prediction is made to where the human gaze will focus and produces results relative to predictive eye-tracking heat maps (Figure 6.11) (Cornia et al., 2018). An example of online machine-generated eye-tracking is `https://expoze.io/`.

Figure 6.10. Generated faces with the styles produced by one latent code (source) override a subset of the coarse styles of another one (destination) (Karras et al., 2018).

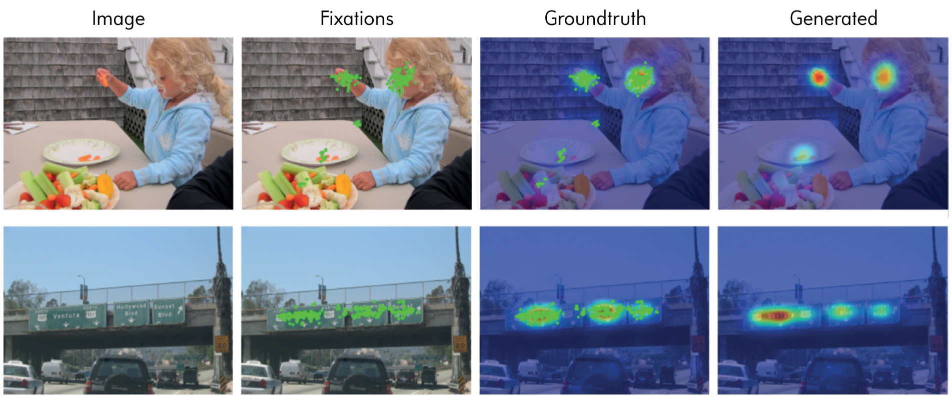


Figure 6.11. Predicted and real visual saliency maps (Cornia et al., 2018).

Generating personas

Personas are "virtual users" (Hosono et al., 2009) that represent target users (Miaskiewicz & Kozar, 2011) to personify user characteristics for design and marketing (Sinha, 2003). Personas help mainly for focus, prioritisation and challenging assumptions (Miaskiewicz & Kozar, 2011).

Personas made by machine could lead to different results as made by humans. This could be inspiring and/or insightful. A collection of personas are used to mine for a 'persona wireframe' which are common characteristics and patterns within mined personas. Secondly, data from a project could be use to automatic fill in the wireframe and are new personas generated. The features of personas data mining are useful for summarising user information and completing/complementing personas.

Considerations

There are many different personas such as attribute, context and marketing-driven, and their usefulness is debated (Flaherty, 2018; Klement, 2014). Depending on the needs and availability of resources, the machine can generate the personas or build them together with the designer.

Making the persona is considered part of designing and empathising with the user. In that case, ready-to-use personas would create less understanding. However, Miaskiewicz and Kozar (2011) identified the most significant benefits of personas with a Delphi study. Data mining can assist directly to several benefits by providing quantities, being a different source, automation or processing information (Appendix A6). Aiding these benefits can guide data mining to enhance the way designers use personas. Otherwise, generated personas might risk being too generic and too little user or project aware.

Design critique

Two different personas were presented to the designers in the workshops: a demographic persona and value-oriented persona (Figure 6.12).

Both personas were "easy to use" said Designer K. However, the project influences the potential of the personas, according to the designers. Designer J thinks that broad target groups (e.g. entire Dutch population for a government project) make the demographic information less useful because it will become too generic. Furthermore, Designer K states that niche markets may result in unstable statistics, because it will be based on outliers.

In general, most designers preferred the value-oriented version above the demographic persona. Designer J and Designer D say that demographics do not capture the experience or life of the users. "I would look for trends in the qualitative part" explains Designer J. The designer focuses on the users' point of view and describes that the value-oriented personas fit this goal. However, the value-oriented persona could also benefit from more experience-based attributes, such as actions or user preferences.

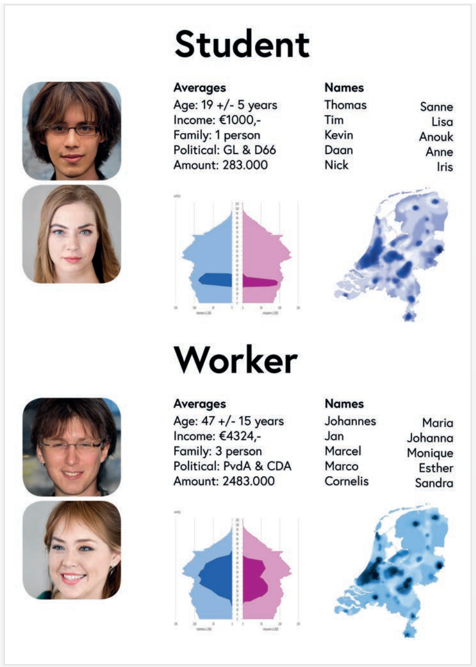
Conclusion

Generating artifacts, designs and (user) tests can aid designers with an alternative perspective, additional information or with efficiency. For inspiring or enhancing generation can existing and additional sources are useful.

Not every artifact is suited for generation method because the result of the generation should contribute. It should be different from the original or replaces a receptive task. In those cases, it will not compete with the designers and their process.

During the design critique, we reviewed the generated personas. Part of the discussion was about the desired characteristics of personas. The designers valued qualitative details that captured the experience of the fictive users, and generated content can add much value when it is based on the real data of such experiences.

(a) Value-oriented persona. Profile pictures from (Karras et al., 2018) and tweets from (Milou, 2019; van der Ent, 2019).



(b) Demographic persona. Profile pictures from (Karras et al., 2018) and infographics based on (CBS, 2018; Spoon, 2009).

Figure 6.12. Fictive generated personas for the PTC case

Method

Segmentations

6.5.4. Segmentation

Segmentation by machine could lead to different results as made by humans. With *Segmentation*, data mining could provide more, easier or alternative insights about the target. The value of alternative segmentation is not only what the alternative segments are, but mostly why these groups are made this way. Users, stakeholders, products, services and other subjects could be segmented. The data could include more behavioural data to research empathy and experience.

Example 6.7

PTC

Public transport company, part 6

Hypothetical case

Designer Luciana and data analyst Minji take a look at the facilities of train stations for PTC. Minji used the data of Wifi-tracking to know anonymous individual walking routes of passengers. They use segmentation to identify the main walking behaviours: waiters, wanderers, schedulers and others. Luciana visits a station and sees if she can identify the patterns. For each behaviour groups, the designer observes, targets and interviews passengers.

After mapping needs, wishes and behaviour, she makes a survey together with the user researcher. In the survey, the identified needs, wishes, behaviours, location and train-station are subject. They distribute the survey broadly and share the many replies with Minji. She performed some pre-processing of the data and again segmentation.

This time they could find relations between the behaviour, train-station and valued/missing facilities. They see that the main differentiating factor is the size of the station. The big stations serve all behaviour segments, but in small stations, the scheduler behaviour is dominant and divided over multiple need segments. Interestingly, these need segments were earlier mapped with different behaviour groups. For example, wanderers prefer open spaces, shops and nature elements. In small stations, there are many schedulers with these needs of wanderers. Luciana proposes that in the smaller stations, the facilities do not match the opportunities for original waiters or wanderers, forcing them to become schedulers.

The visuals and quantities of these segments help designer Luciana convincing stakeholders to investigate the facilities of smaller train stations further. She will continue with finding the waiter or wanderer passengers in disguise.

Overview

Murray et al. (2018) discuss three segment-strategies: top-down, attribute-based and behaviour-based segmentation. The top-down method learns from the product and projects it models down on the individuals and therefore, can not detect underlying demand signals (Murray et al., 2018). In contrast, attribute-based segment forecasting makes segments based on attributes associated with the customers, such as demographics, but is highly dependable on the variables to describe underlying behaviours (Murray et al., 2018). Attribute-based clustering is, for example, used for marketing to boost cross-sales by identifying target profitable and reliable customers (Köksal et al., 2011; Witten & Frank, 2005). These attribute-based insights are interesting for service designers, but behaviour-based insights are more experience related. Behaviour-based segmentation analyses the actual behaviour patterns. It produces better detection of behaviour segments because different descriptive attributes sometimes exhibit similar behaviour (Murray et al., 2018).

The machine-generated segments could break traditional marketing segments with alternative and behavioural insights, such as the labels 'student' and 'adult' did not match the public transport user behaviour (Agard, Morency, & Trépanier, 2006).

By clustering the Canadian public transport card data, Agard et al. (2006) detected non-traditional segments. Adults and especially students have various behaviours and belong to different behavioural segments (Figure 6.13). They produced these behaviour-based groups by combining two cluster algorithms: k-mean clustering as input for a hierarchical clustering technique called Hierarchical Ascending Clustering (HAC).

Wang, Zhang, Tang, Zheng, and Zhao (2016) also produced behavioural-based clusters with a hierarchical clustering approach but developed an interactive app to explore the results (Figure 6.14). They discovered general and key user behaviour patterns in clickstreams of users from a popular anonymous social network app.

Segmentation can find 'new' segments because it has not trained on existing groups. It works without categories or labels defined a priori (unsupervised) and therefore captured unexpected or previously unknown user behaviour (Wang et al., 2016). The results as qualities (sexting correlates to user blocking[3]) and quantities (80% of users spend more than 10% of their total clicks on blocking events[3]) are useful for the designer as an insight but also evidence and foundation for non-traditional segments.

K-means clustering

Clustering into k groups by selecting the nearest mean for a new item.

Hierarchical clustering

Clustering by defining a three-like hierarchy of clusters.

Clickstream

Click sequence of a user navigating trough one or more websites.

Unsupervised learning

Learning from data without labels, aka learning without predefined correct answers to learn from. Antonym of Supervised learning.

Considerations

Noteworthy is that the data must be rich enough to prevent self-fulfilling prophecies. For example, if the data of bags of chips only contains the features used for current marketing groups, then the segments produced by data mining are probably exactly like the original are defined: by sub-brand and main taste.

A similar effect applies to the attribute versus behavioural segmentation. The results are dependable on the variables to describe underlying behaviours (Murray et al., 2018). The segmentation can not use the features that are not present; only the invisible patterns between the features can be revealed. For instance, using different attributes or data sources can help in detecting these unknown patterns.

[3]Segmentation insights from Whisper app by (Wang et al., 2016, p. 226).

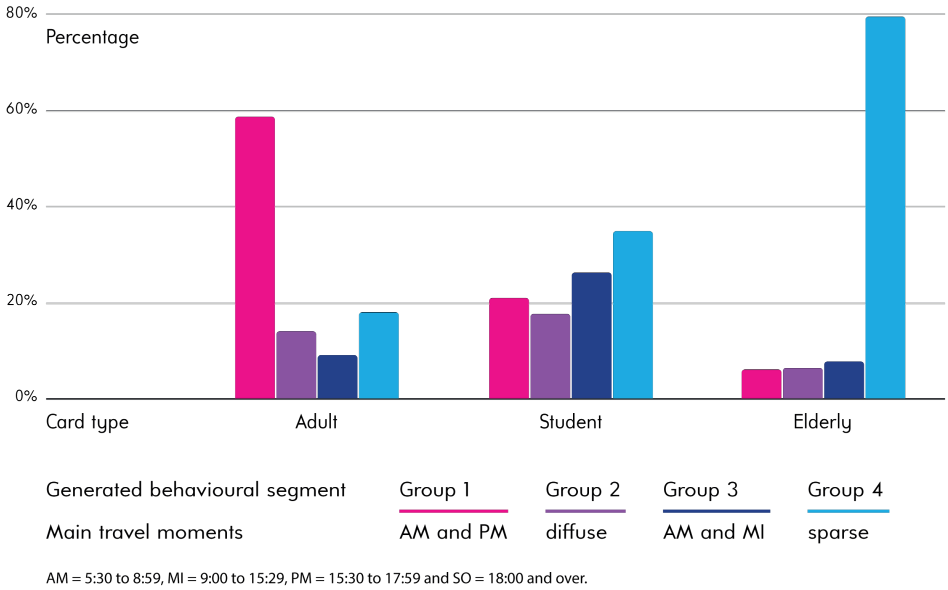


Figure 6.13. Distribution of the four behaviour clusters percentages per card type. Constructed on results of (Agard et al., 2006).

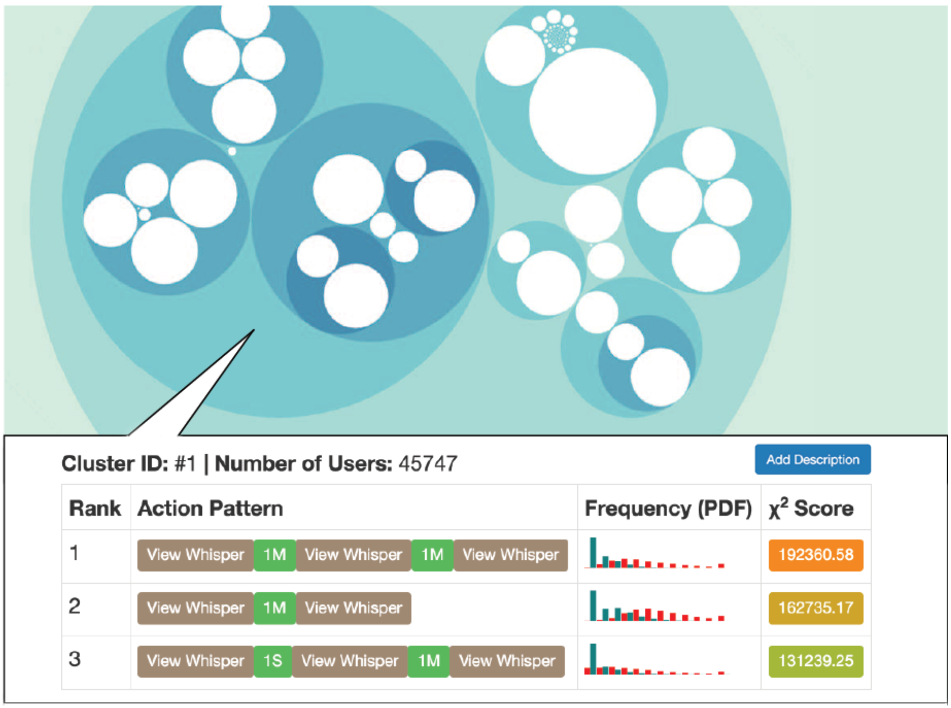


Figure 6.14. Whisper behavioural clusters with cluster 1 in the pop-up window (Wang et al., 2016).

Design critique

During the workshops (Section 6.2), the designers made each differently evolved versions of the presented version (Figure 6.15). Designer F ignored the ability to generate segments and preferred user groups as defined by the stakeholders. "Can I compose the group? I would like to know about my focus group" Designer F said. The designer sees a use for such a system during the project to keep insights specific for the defined scope.

Designer A imagines that the original version of generated segmentation is used for insights that need further investigations. The segmentation would be used by Designer A to find what users with problems have in common. The results are a starting point and will be checked with stakeholders by Designer A, next they help to keep focus.

In an evolved version explores Designer A, as a designer, the correlations between features. "I would love to pin one specific variable and click trough other variables to see what groups emerge". The designer carries on and imagines the possibility to pin an emotion. In that case, the designer prefers that the machine generates knowledge: "Than I see all the associations with that emotion. *What forms those segments?*".

While the discussion continues about associations and correlations, Designer A is afraid that the meaning of causality is misinterpreted or that noise inadequately is presented.

Conclusion

By segmenting a collection of individuals can attribute and behavioural patterns be detected, and groups formed on non-predefined characteristics. It provides an alternative view of the segments and insights about the users or products because unexpected or detects previous unknown user behaviour.

Different segmentation strategies exist, and the collection of data should match the strategy. In order to prevent self-fulfilling prophecies, the data should be broader than known factors. During the design critique, designers showed the most interest in behavioural- and emotional-based segmentation. Conclusions such as correlations were also valued.

The insights from why the groups are formed this way seemed to hold more value than the new groups themselves. Partially because target groups are defined by stakeholders, but also because understanding the user is more important. An interactive system could contribute to understanding the data by exploring, such as Designer A described. Designers could also explore self-made groups in the interactive application.

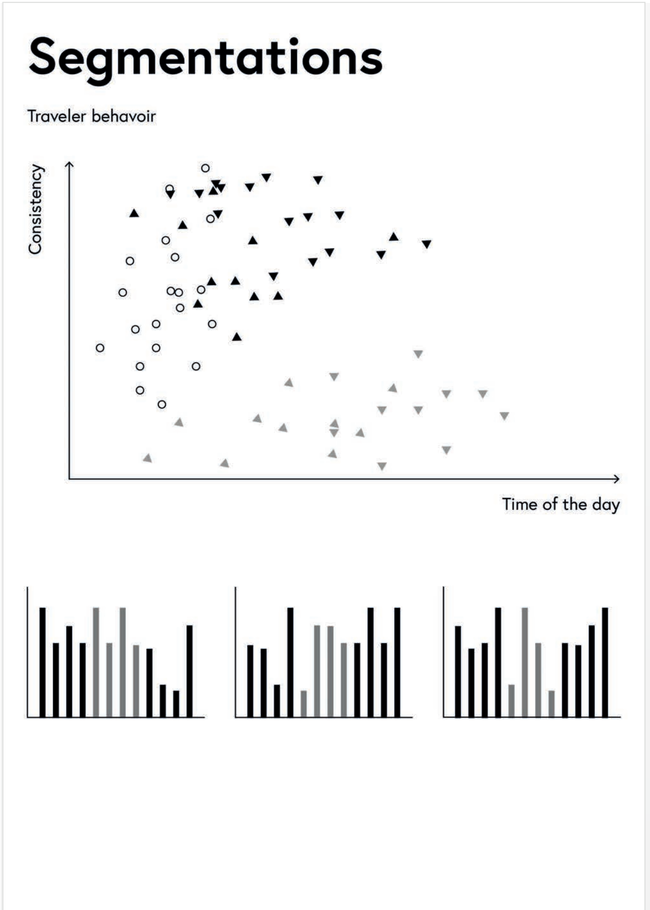


Figure 6.15. Fictive segmentations for the PTC case

6.6. Collaboration

The last category takes a closer look at the collaboration between designers, data scientists and data analysists as a team. This full-time, part-time or temporary team consists of designers, user researchers and/or data scientists.

This section will discuss methods for requesting information in a broad sense as *Data mining on request* (Section 6.6.1) and for detailed information in *Q&A and validation* (Section 6.6.2). *Combining for context* (Section 6.6.3) boosts the quality of data mining, while *Visualise* (Section 6.6.4) helps to improve the communication about data mining results.

The *Collaboration* methods evolved during the research process, similar to the other methods (including the first round feedback round). However, the *Collaboration* methods were eliminated from the final iterations and workshops because they fitted no longer the scope of the study, as is discussed in the research process: (Section 4.2). This category will still be discussed but contains less depth.

Furthermore, it is noteworthy that close collaboration and teamwork probably leads to better results. Although collaboration might sound self-evident in a cross-disciplinary team, in practice might different disciplines have different expectations. General (multidisciplinary) team-building methods, such as a defining common ground, communication techniques and meetings, are not discussed in this thesis.

6.6.1. Data mining on request

Method

DM on request

The designer provides input about subjects of interest, and the data scientist uses its expertise to mine for prominent and interesting patterns. This method has an exploratory nature. The designer simulates the data scientist but the data scientist experiments and follows her/his instinct. The typical requests are analysing, summarising or predicting based on available data.

The complexity of the request depends on the team, data and needs. An entry-level is a basic statistic overview of the dataset. More relevant insights require more input, discussion and/or experience between the data scientist and designer.

6.6.2. Q&A and validation

Method

Q&A

During the design process, the designer questions findings, assumptions and situations or simply wants to know more. With *Q&A*, the designer proposes a specific question or hypothesis which the data scientist tries to answer within the available resources (time, data, etc.). This method can be used to satisfy the curiosity of the designer, such as testing an assumption. Another goal is to validate or support other results and design decisions.

Method

Combining for context

6.6.3. Combining for context

As discussed in *Complementary expertise* (Section 5.1.2), the designer can provide expanded domain knowledge with a holistic view for effective data mining. With this view, the designer uses a comprehensive understanding of (proposed) possible influences. Furthermore, the designer can help to create value for the user and stakeholder. By sharing and gaining knowledge, the data scientist and designer increase effectiveness and meaning of data mining.

Example 6.8

PTC
Public transport company, part 7
Hypothetical case

In Example 6.4, Anne and Olivia applied *Combining for context*:

At PTC, the transportation system uses applications for planning or monitoring traffic. Data scientist Anne analyses the process mining model based on the logs. *Service designer Olivia assists Anne in prioritising the results. She detects which problem areas influences the user experience.*

The design team focuses on this issue that conductors sometimes do not have enough time for inspections, and it is unclear if or why the planning systematically falls short. *Based on experience and domain knowledge, Olivia proposes factors that might play a key in the seemingly irregular delays. Then, Anne uses the models to validate these ideas.* As a result, they discover that the planning did not match with the actual time spend when inspecting in a specific type of vehicles.

Method

Visualise

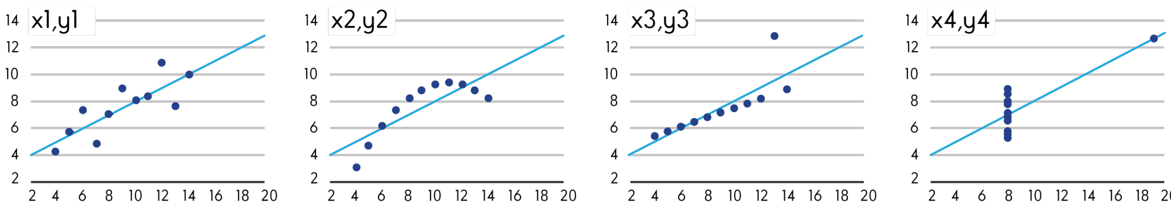
6.6.4. Visualise

Visualisations are a familiar tool for designers and service design has a highly visual approach (Costa et al., 2018). Relevant data can also be visualised for effective communication, organising, understanding, reasoning, decision making and displaying correlations (van der Aalst, 2014a; Costa et al., 2018). Visual models can furthermore result in inspiring representations or providing a different angle. The *visualisations* are useful within the team, but can also be used to inform or convince stakeholders.

Visualisations can inform and communicate better as result of cognitive advantages, as described by van der Aalst (2014a): increasing cognitive resources, representing a large amount of data in a small space, enhancing the recognition of patterns and providing a manipulable (and interactive) medium. Figure 6.16 demonstrates that visually distinguishable data can have similar statistic measurements.

Visualising tools are readily available[4], easy to use and understand. Therefore the design team can use visualisations to communicate about data and results within and outside the team.

[4] Tools exist in the range of general (e.g. spreadsheets) to specialised tools such as Tableau, Domo and Dundas BI.



The $mean_x$, $variance_x$ & $correlation$ are the same and the $mean_y$ & $variance_y$ are similar in four sets.

Figure 6.16. Anscombe's Quartet is four datasets with the same statistical properties (Anscombe, 1973). The visualisation shows the differences between the data. Visual based on (van der Aalst, 2014a; Tufte, 2001).

Part IV

Conclusion

Chapter 7

Discussion

During this study, I researched the means through which data mining can support the service design process. This qualitative, explorative study resulted in a guide to data science methods for service designers that contribute to the diversity of the designers' methodology toolkit. To our knowledge, this is the first approach that explicitly examined data science methods in the direct context of service designers. Particularly, practitioners evaluated the method concepts.

These data science methods for service designers demonstrate that data science assists the service design in four main ways:

A. Data mining can make hidden information accessible to designers with specialised user research tools (Section 6.3).
B. Data mining can help designers in their creative process through relevant resources, inspiration and an alternative perspective (Section 6.5).
C. Process mining can support designers with understanding and testing models of systems, such as the customer journey (Section 6.4).
D. The design team can gain new insights about applications and users from collaboration with data scientists or analysists (Section 6.6).

In addition, these findings provide additional information into the general contribution of data science to design (Chapter 5):

E. Data mining can increase the validity of user research with method triangulation.
F. Integrating data science techniques requires organisational maturity, which influences the possibilities and challenges of combined projects.

7.1. Research implications

Together these results have the potential to enhance the methodology toolbox of service designers and encourage organisations to mature with data science resources and capabilities for design projects. For example, advanced user research tools need development, and relevant data must be collected. Service design and user-centred design fields can benefit from these developments by becoming more informed about the users, stakeholders and applications. Furthermore, new challenges, employment and consulting for data scientists/analysists arise to support the advancing designers' needs.

The current section discusses the implications of this study from general to specific: integrating data mining and design projects (F, D) validating user research (E), advanced user research tools (A), complementary inspiration and perspectives (B) and models of intangible designs (C).

Integrating data mining and design projects

Integrating data science depends on the organisational structure of the project teams and the overall data science maturity. Companies and clients should invest in infrastructure and capabilities to use data science for design projects.

Integrating data mining into design projects will change the roles within design teams and user research, as discussed in Section 5.2.1. For example, teams need to acquire quantitative and qualitative roles. The increasing diversity of skillsets will improve the available methodologies, but requires a new way of working.

Furthermore, integrating data science techniques requires organisational maturity in data science. Organisations need to transform and keep investing maturity. This will lead to new opportunities for growing teams and companies (Section 5.2.1). With developing maturity, the availability and quality of data for service designers will grow and improve the designs they make.

Addressing the maturity of clients is also essential for (design) agencies. Since they depended on the data and recourses of their client, the agency can consult about data, data science and the integration with design.

Validating user research

Data mining can increase the validity of user research with new methodologies for method triangulation. Design teams should check and update their research methods toolbox with data science empowered methods.

Design teams should critically look at their user research and check if data science can fill their triangulation gaps and/or make their user research more effective. Section 5.1.1 explains that a variety of methodologies is essential for the designers to achieve holistic and valid observations, and to ensure applicability and quality in a range of projects. For example, the design team should cover behavioural-attitudinal and quantitative-qualitative axis. As a result, the designers' insights and methodologies are more robust.

Advanced user research tools

Some insights are hidden because it is inhuman amount to process, or the signal is too subtle to notice humanely. Data mining could help make these insights available with specialised research tools. These tools should be built and used.

More advanced user research tools become available, and design teams can create a better understanding of user behaviour and inner states (Section 6.3). With this improved knowledge, the services adapt better to the user and improve the user experience.

Complementary inspiration and perspectives

Data mining can help designers in their creative process with relevant resources, generative design and an alternative view. Therefore, the design process will be more efficient and based on more perspectives.

With generative design, more digital creative tools become available and result in new insights about the users and designers (Section 6.5.3). For example, non-traditional segments based on behavioural patterns provide alternative user-groups, as discussed in Section 6.5.4. This will improve the service design process itself as designers utilise more or better resources.

Analysed data from the explorer or data-driven design system results in new insights about the users and designers (Sections 6.5.1 and 6.5.2). With these insights, teams increase the domain knowledge and spread knowledge faster through the organisation.

Models of intangible designs

Process mining can support designers with understanding and testing models of complex systems, such as the intangible customer journey. Designers will gain more insights into the real-time journeys of many users.

Service designers can use process mining and data science techniques to model for insights and prototypes in complex projects. They will understand the practical implementations of their design decisions because of the better comparison between the actual and aspected journeys (Section 6.4). Service providers can expect better feedback on the implementation of their services. This will not only improve the designed services but also implementing the services.

Chapter 8

Conclusion

This research aimed to identify the opportunities for data mining to support service designers. The iterative research process resulted in a guide to concepts of data science methods for service designers. The research development covered both fields in academic and in practice. Moreover, it included the participation of designers in workshops. By analysing these concepts, this thesis has shown the diverse ways data mining can support the service design process.

Service designers use particular methods to collect and analyse information for creating a holistic view of the users and stakeholders (Chapter 2). Data mining supports by adding techniques for access to new insights or increase validation by aiding method triangulation (Chapter 5). The techniques analyse for patterns, correlations and answer contextual or desirability questions (Chapter 3).

This research identified four ways for data science to assists the service design process: 1) specialised user research tools, 2) inspiration and resources in the creative process, 3) modelling complex systems and 4) new insights trough interaction with data specialists (Chapter 6).

Challenges for using these concepts and methods are mainly organisational maturity related (Section 5.2). Selecting a matching technique (including the data) depends on many factors, which became evident with the consideration and options of the concepts.

This research is an explorative and qualitative study and presents a broad overview. The concepts are related to the needs of designers and available project resources (Section 6.1). The results are useful to orient and select data mining techniques for service design projects, but the findings can not be generalised.

The research evaluated with designers from the company Mirabeau, an agency that practises service design (Section 2.2.2). Future research must investigate with practitioners from other organisations (e.g. in-house vs outsourcing). Future studies could also continue to examine the viability, practical application and hands-on information of the methods.

In conclusion, this research provides key information in an overview of data science techniques for service designers and their design process. Where fragmented literature might provide useful insights, this study offers validation with service designers or explicitly addresses their needs. The overview and the methods assist design agencies, such as Mirabeau, service designers and their teams in organising, selecting and utilising these data mining techniques.

8.1. Answers on the research questions

This research aimed to help service designers and their organisations with orienting and selecting data mining techniques for their design projects. Therefore, I defined the following research question: When and how can Data Mining be used to support Service Designers?

It is essential that the research meets the needs of the designer and fits the design process. Furthermore, it should address the feasibility and include a theoretical foundation for data mining techniques. Accordingly, these two aspects are examined in the two subquestions: 1) What does the Service Design process need? 2) What can Data Mining offer?

This section answers the subquestions, followed by the main research question.

Subquestion 1

What does the Service Design process need?

Service designers need expanding their toolbox with diverse methods for collecting data and generating insights to create a holistic view.

The *Service Design process* (Section 2.2.1) is a non-linear iterative process of diverging and converging activities. Most service design processes relate to two stages, where first, the problem is researched and defined. Then secondly, designers create, evaluate and deliver the solution. Designers use methods during the project to create a holistic understanding by collecting data (user research), create ideas by connecting insights and test concepts by user-centred measuring.

This research introduced more tools to help service designers improved their user research. An extensive collection of methodologies, such as wide variety in available methods, sources and subjects, is essential for achieving complete, holistic and valid observations and generating ideas. A diverse toolbox increases the applicability, flexibility and the validity of the methods and their results.

Subquestion 2

What can Data Mining offer?

Data mining offers new methods with powerful analyses for more accessible, previously unavailable and/or contrasting information.

This thesis presented concepts in which data mining aids method-triangulation and supplies more and different sources and methods for information to service designers. Data mining reveal previously hidden or unavailable information because it finds new patterns in (inhuman) large data collections. It is mainly quantitative-based, and the machine has contrasting features compared to humans. Data mining makes it possible to process more, faster and differently. Therefore, designers access with data science easier, new or different information.

The overview of the methods demonstrates this variety of ways service designers can advance their design process with data mining and data science. For example, *Bio translations* (Section 6.3.2) showed that data mining still detects seemingly small patterns in users. *Segmentation* (Section 6.5.4) is an example of using data mining directly and provides an alternative perspective about users or applications. Furthermore, data science can apply to any subject a designer encounters, such as materials and tools designers use in *Generating artifacts* (Section 6.5.3).

When and how can Data Mining be used to support Service Designers?

Main research question

Data mining can be applied during the whole design process. It offers new ways for designers to find and analyse information or inspiration. This will result in additional insights and validation for the holistic view and/or a more efficient design process.

The service design process distinguishes different phases that are research-heavy and analyse users and systems (e.g. understand and test). It makes sense that data mining fit these phases well. However, this research showed that data science also supports designers outside this scope (Section 6.1.2). Directional research and small iterations ensure that testing and research also occur in other phases. Furthermore, design teams can use data mining indirectly in tools during the whole project. Data science can additionally stimulate inspiration during the ideation phase, as discussed in *Serendipity* (Section 6.5).

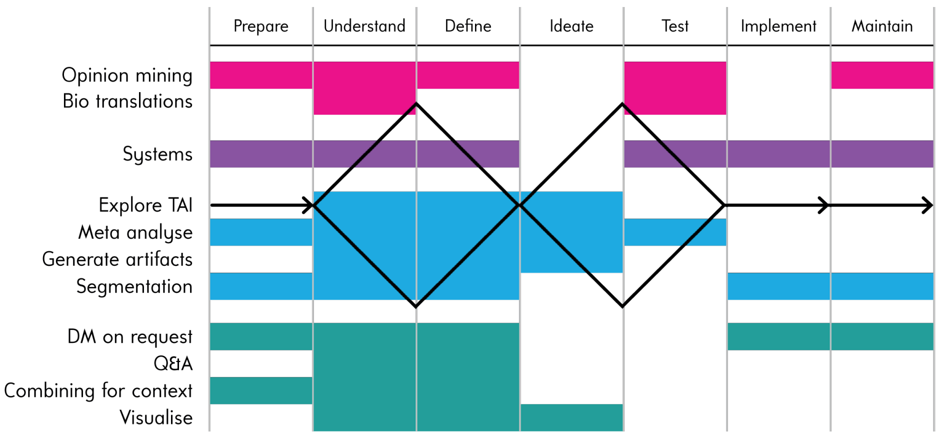


Figure 8.1. Methods in the design process. The most relevant phases of each method are highlighted.

Data science supports user research in both foundational and directional research. It provides techniques that find patterns, correlations and overview for a complete picture of the users, such as *Opinion mining* (Section 6.3.1) and *Segmentation* (Section 6.5.4). User research is vital for analysing the holistic experience, and service designers benefit from specialised user research tools to reveal new information about the users (Section 6.3).

Furthermore, data mining aids with techniques for validation and specific contextual or desirability questions. Examples are *Q&A and validation* (Section 6.6.2) and *Data mining on request* (Section 6.6.1). Process mining can support designers with analysing specific bottlenecks or understanding and testing models of the customer journey (Section 6.4).

Data mining can help with the fast collection of materials that designers gather and build by finding patterns, highlighting elements and analysing insights. This approach is useful for overarching projects in *Explore Tools, Artifacts and Insights* (Section 6.5.1). Also with *Bio translations* (Section 6.3.2), certain interesting parts of recordings are automatically preselected. Additionally, data mining supports the creative process through generated designs or alternative perspectives that inform and inspire designers (Section 6.5).

Finally, data scientists answer specific questions, hypothesis or explorative requests of designers in full-time, temporary or remote teams (Section 6.6). The methods demonstrate that data mining supports indirectly in tools or direct with tools, custom software, and collaboration in teams.

The concepts for data science methods for service designers depend on different levels of organisational maturity. The required capabilities, such as skills and data, differ per technique. For example, one method expects only statistical knowledge, while another involves expert knowledge in process mining.

Similar to conventional experiments, the selection and quality of the data influence the results of data science. Some data might contain biases such as the participation biases of consumer-generated content. Furthermore, the data should be rich enough to prevent self-fulfilling prophecies. In the case data is not available, the team can initiate collecting the data, turn to other (public) data or be creative.

Selecting a matching technique for the project does also depend on the designer's needs. Before applying, the teams have to consider the options and limitations of the selected technique. For organisations with a low maturity level, acquiring the right capabilities and data is particularly challenging.

In conclusion, this research introduced an overview of concepts that aids service designers and their organisations get started with adding data mining to their design process. Although their process will not change, the new methodologies will improve the available knowledge and validity, ensuring better holistic understanding, experiences and co-creation of value for the user and service provider.

8.2. Research limitations

The list of methods is comprehensive but not complete. It functions as an overview that fits a broad audience. The methods are related to different stages in the organisational maturity, the design process phases and project resources. This research is limited by the concepts with the involved organisations (Mirabeau), criteria (desirable and feasible) and the used methodology (explorative and qualitative).

The concepts were tested with the company Mirabeau, an agency that is not specialised in service design. Still, the interaction and 'digital service designers' at Mirabeau use the service design process, as discussed in *Design at Mirabeau* (Section 2.2.2).

The amount of involved organisations is low, and other service design companies or companies with in-house service design were not included in this research. The validity of the designers' needs and the applicability of the study would increase if more organisations were involved.

The research process of this study contained many iterations to create over thirty concepts, which were repeatedly criticised and reduce to the 'final' methods. Criteria for these methods are related to the "innovation sweet spot" aspects: viability, feasibility and desirability (Orton, 2017; Castillo, Diehl, & Brezet, 2012; Menold, Simpson, & Jablokow, 2016). Although the final criteria overlap with the sweet spot[1], this research had a clear scope and did not address all innovation aspects equally.

This study does not discuss the viability in great detail. The methods are concepts, and the described performance depends on many unelaborated factors.

When the applied case was cancelled, the technical depth of the research lost priority. Still, the technical feasibility of each method is substantiated in this thesis from literature and hypothetical perspective. Existing literature proved the theoretical technical foundation of the methods. In contrast to the literature, this study used designers to evaluate the results.

The desirability of the concepts was evaluated together with the participating designers. In the workshops, this research examined the possibilities and use of the methods from the designer perspective. During the research process, desirability gained priority, and I adopted a new focus to connect the methods to the designers' daily lives. This focus resulted in evaluating the purpose of using design methods, such as gaining a useful outcome.

The 'final' methods received an unequal amount of evaluation due to time constraints, as elaborated in the *Research process*. The additional selection criterium 'Independent' excluded methods for the workshops. The method should be explainable without dependence on data science because the workshops are more effective when the designers only have to relate to their part.

[1] The three evaluation criteria were: 1) Clear; what and how the method works should be evident 2) Desirable; the method meets the needs of the designer and fits the design process 3) Feasible; the method includes a theoretical technical foundation.

As a result, methods from the *Systems* (Section 6.4) and *Collaboration* (Section 6.6) categories are less validated, and in case of *Collaboration* also less detailed since they use no specific technique. The selection criteria excluded these categories for practical reasons and not because independent methods are preferred.

The feedback sessions and evaluation workshops, in which the designers participated, influenced the concepts of the methods. During the workshops, I used mainly qualitative techniques with a modest amount of designers to verify the feasibility and desirability of the methods. This study primarily examined the attitudinal response to several variations of a concept in a hypothetical case. Therefore, the results do not address the actual use of the techniques applied by service desigers. Increasing the number of workshops, participants, and establishing the viability, feasibility and desirability equally, would substantiate this research.

8.3. Future work

Future investigations are necessary to build up and advance the concepts that resulted from this study. Each method concept or category needs further research into the practical application or hands-on information for designers and their team. Validating within the designers' context is essential, and case studies and/or participatory design is recommended.

The research evaluated with designers from the company Mirabeau in workshop sessions, as described in the *Research process* (Chapter 4). Future research must investigate with practitioners from different organisations. Furthermore, method triangulation will increase the validity of this research, which mainly used low-scale, qualitative, attitudinal responses.

Future research could further examine the current state of data science and design maturity in organisations and clients. This research encountered the importance of data science maturity of organisations because low maturity could lead to technical, organisational and other challenges. However, the scale of low-matured organisations is not addressed. Further research could map the most significant challenges, best practises and maturation of the present field. Based on Corsten and Prick's Maturity model (2019), the following factors can assess the methodology adoption: people & recourses, tools & capabilities, organisation structure and metrics & deliverables.

This research focused on stand-alone, relative independent, techniques for data science to support the service design. Other approaches for bringing the fields together might be a topic for future studies. For example, the direct collaboration between design teams with data scientists is still in their early stages. The roles within design, data science, qualitative and quantitative user research are developing and benefit from insights into the current state and best practises for the future.

Acknowledgements

I want to thank Mauricy Filho and Lennart Overkamp for surpassing their role as supervisors.

Mauricy has been enthusiastic from the very beginning, which gave me the power to aim for this ambitious research. I value his guidance through each stage of the process and his effort to join meetings in Amsterdam.

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Honestly, I could acknowledge my husband, Jasper van der Waa, for the whole master. Without his support, I would have never started or finished this big adventure. Leaving my adult life behind to start all over was not easy, but being left behind must also be hard. Jasper encourages me, and I look forward to our new adventures.

Finally, I would like to thank my close family and new friends, such as my mom, Laris, Rianne, Daniël, Jonne, Nathan and Jelte.

Part V

Appendix

Appendix A

Appendix

The following sections are included in appendix A:

A1. Maturity model

A maturity model guides and identifies the steps in the process of embedding a new methodology into organisation, such as service design. I propose to adopted the maturity model of Corsten and Prick (2019) and extract the following five stage maturity model for data science and design:

Explore

This first stage is about trying the new methodology and starting the initiative.

What it's like	What to do
There is nothing yet: no responsibility, no budget, no time and no facilities.	Start exploring with a small multi-disciplinary engaged group. Tip: do not ask for permission yet, since there is a risk of prematurely killing the movement.

Prove

The second stage should create evidence of value and lay the foundations.

What it's like	What to do
The small group starts a multi-disciplinary project team.	Demonstrate the real business value with (experimental) projects. Tip: place the focus on results instead of process and use recognisable business terminology for new projects to the organisation (or even trojan horses).

Scale

In this stage, the capabilities stead outside the initial team and expand through the organisation.

What it's like	What to do
More initiatives and multi-disciplinary project teams arise.	Create a common methodology for a unified language and guide unaligned initiatives. Tip: train the methodology to the organisation in different levels such as basic literacy, advanced application and leadership.

Integrate

The fourth stage systematically integrates the methodology in daily way of working.

What it's like	What to do
The capabilities is now decentralised and present in each team.	Build a communitie to maintain the unified way of working and share new knowledge. Tip: use systems to stimulate consistency, innovations and prevent repetitive and similar work.

Thrive

The last stage ingrains the methodology into company culture and pushes the field.

What it's like	What to do
The C-level is involved in carrying out the new way of working.	Take care of the culture and core principles while nurturing innovation and building a community. Tip: thriving is now about spreading, inspiring and recreating the game.

A2. Holistic and integrative aspects

As descibed in *Definition of Service Design* (Section 2.1), service design contains the holistic user experience. This section will discuss the holistic characteristics of service design from perspective of the customer experience and the integrative approach.

Service designers view the customer experience as holistic, where the holistic experience is:

Temporal
The services are preformed and its processes take place in time (Halvorsrud et al., 2016; Yu & Sangiorgi, 2014). "A service can be thought of as a set of choreographed interactions between a customer and service provider" (Forlizzi & Zimmerman, 2013, p. 2).

Multi-sensory
Users experience (subconsciously) with all senses (Pullman & Gross, 2004; Stickdorn et al., 2011) and service designers design for those senses (Zomerdijk & Voss, 2010).

Emotional
Designers want to understand how users feel about the service (Yu & Sangiorgi, 2014), because the tangible environment evokes particular emotions and responses (Zomerdijk & Voss, 2010).

Intangible
Service designers aim to create a comprehensive overview of the complete situation, including metal, behavioural and other intangible contexts. The experience and service are intangible (Zomerdijk & Voss, 2010; Secomandi & Snelders, 2011) and tangible and intangible resources form the basis of value-creation (Patrício et al., 2018).

Tangible
Although the service itself is intangible, it is perceived though the tangible world (Zomerdijk & Voss, 2010; Kimbell, 2011; Stickdorn et al., 2011; Secomandi & Snelders, 2011). The service is designed by designing the tangible: interface, sociotechnical resources, artifacts, service evidence (Secomandi & Snelders, 2011).

Cross-channel
Service providers interact with their customers through the use of customer channels (Sousa & Voss, 2006; Osterwalder, 2004) or alternately, service interfaces (Rayport & Jaworski, 2004). Customers use multiple channels and frequently switch or combine (Halvorsrud et al., 2016)

Relational and social
Context consists, besides the tangible, relational elements (Zomerdijk & Voss, 2010) such as underlying relationships, roles, and agendas (Forlizzi & Zimmerman, 2013). Designed service systems respect social, material, and relational aspects to make meaningful value (Yu & Sangiorgi, 2014; Kimbell, 2011).

Additionally, a holistic experience can be:

Digital
Next to the tangible, play digital actors a role in services (Kimbell, 2011). Digital interactions, touchpoints, artifacts, channels and mediums could be part of the journey (Halvorsrud et al., 2016; Stickdorn et al., 2011).

Societal
Services have a transformative power, also over society and economy (Sangiorgi, 2010) and service design can tackle societal level problems (Forlizzi & Zimmerman, 2013).

The analysis of the service provider and its relations holds key to the service as well. Service design concerns the integrative view of environment, people and activities to deliver service (Yu & Sangiorgi, 2014). The integrative approach includes:

Infrastructure
The infrastructure is part of services (Secomandi & Snelders, 2011; Yu & Sangiorgi, 2014) and include employees, customers, stakeholders and designers (Goldstein et al., 2002) and their organisation.

Stakeholders
Service designers relations between stakeholders because they are part of the co-creation of value (Forlizzi & Zimmerman, 2013) and are concern the experience (Costa et al., 2018), engagement (Yu & Sangiorgi, 2014) and relations (Forlizzi & Zimmerman, 2013) of the stakeholders involved.

Organisation
The service provider arranges the service by organisation of systems and people (Yu & Sangiorgi, 2014) and services are involve with many departments, such as management, marketing and operations (Patrício et al., 2018; Kimbell, 2011). In order to offer or improve services, the organisation might have to transform (Sangiorgi, 2010; Yu & Sangiorgi, 2014).

Structure
The structure of a service are the physical, technical and environmental resources of both user and service provider such as facilities and equipment (Goldstein et al., 2002; Yu & Sangiorgi, 2014). The artifacts aid this structure and capture the part of intangible facets of services (Secomandi & Snelders, 2011).

Processes
The holistic approach includes processes and activities involved in a broad scale from frontstage (between user and service provider) to backstage (support for frontstage) (Kimbell, 2011). Backstage activities are not directly visible for user and include for example increasing efficiency and control (Zomerdijk & Voss, 2010).

A3. Evolution of the methods

The overview of categories and methods emerged during a game of converging and diverging. In this visual representation are the most prominent methods and intermediate steps shown. The detailed elaboration of the development of the categories and methods is described in *Research process* (Chapter 4).

The following points in time are marked:

Paper cards
The first ideas resulted from an individual brainstorm session, where the ideas were placed next to the design process. Paper fill-in cards were used as an ideation method that makes ideas while addressing their attributes. (page 30)

Digital cards
The paper card proceeded with the new digital version. This digital version was content-flexible and the description improved in this version. (page 32)

Flow diagram
The methods were placed in perspective of the designer. The flow demonstrates how the designers lead to a method. (page 32)

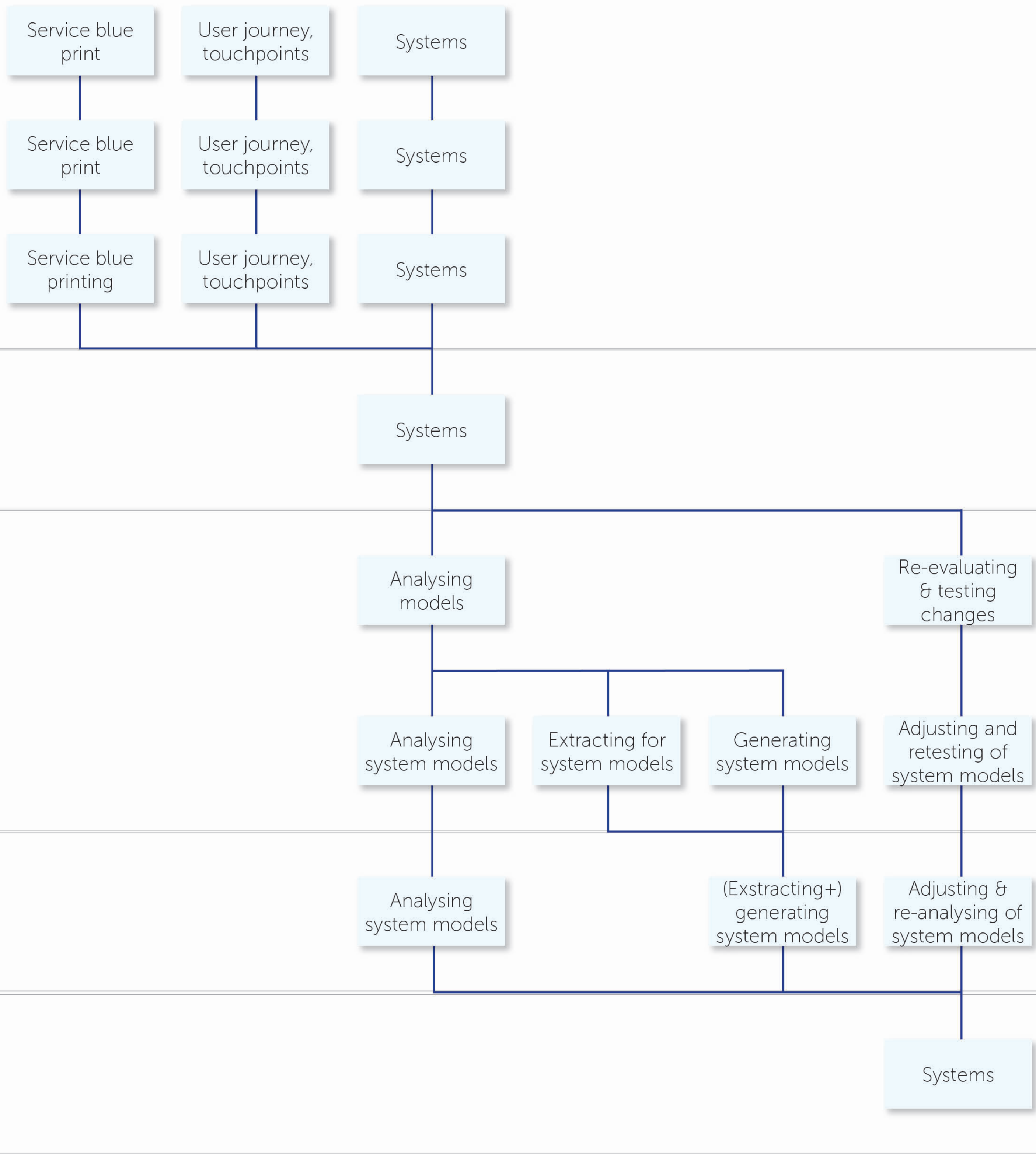
Minimal card
The minimalistic card was designed to efficiently communicate the method in the feedback sessions with the designer. (page 34)

Feedback sessions
The minimal cards were very generic and combined with sketches of examples. The number of cards was decreased by combining similar methods. (page 34)

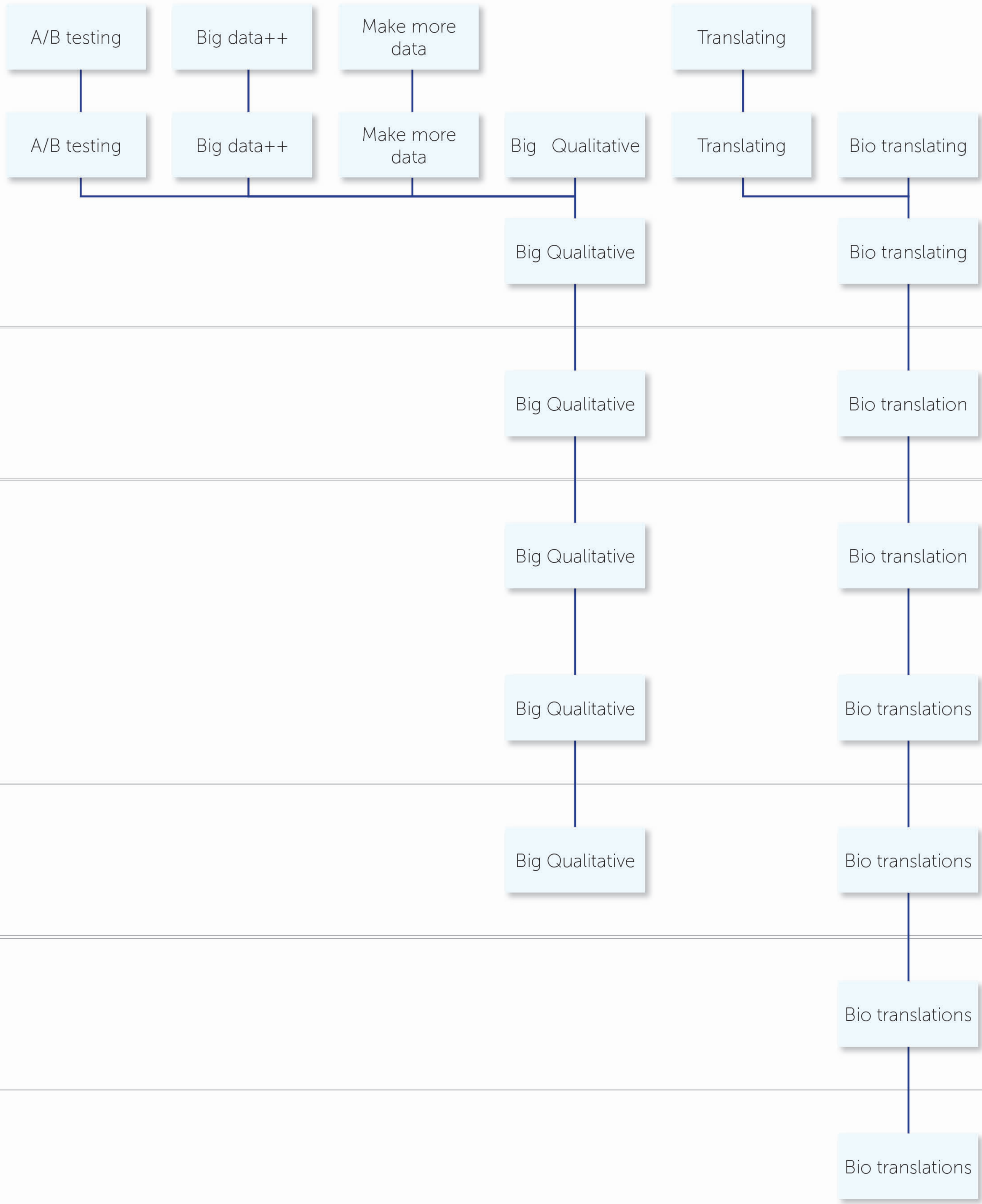
Final methods
The insights from the design feedback and the requirements of the research scope reselected the final methods. The methods had to be clear, desirable and feasible. (page 35)

Workshops
Due to time constrains, only five from the methods were selected for the more detail evaluation during the design critique workshops. The *Collaboration* and *Systems* categories were excluded because of the collaborative and technical heavy natures. (page 36)


Time
Topics
User affection
Validation
Topics
User opinion
Validation
Q&A
Paper cards
19 methods
Trending topics
Validation
Q&A
Digital cards
14 methods
Trending topics
Validation
Q&A
Flow diagram
19 methods
Trending topics
Opinion Mining
Validation
Q&A
Minimal card
24 methods
Trending topics
Opinion Mining
Validation
Q&A
Feedback sessions
15 methods
Opinion Mining
Q&A and Validation
Final methods
11 methods
Opinion Mining
Q&A and Validation
Workshops
5 methods
Opinion Mining
In total 34 idividual methods



Service blue print
User journey, touchpoints
Systems
Service blue print
User journey, touchpoints
Systems
Service blue printing
User journey, touchpoints
Systems
Systems
Analysing models
Re-evaluating & testing changes
Analysing system models
Extracting for system models
Generating system models
Adjusting and retesting of system models
Analysing system models
(Exstracting+) generating system models
Adjusting & re-analysing of system models
Systems


A/B testing
Big data++
Make more data
Translating
A/B testing
Big data++
Make more data
Big Qualitative
Translating
Bio translating
Big Qualitative
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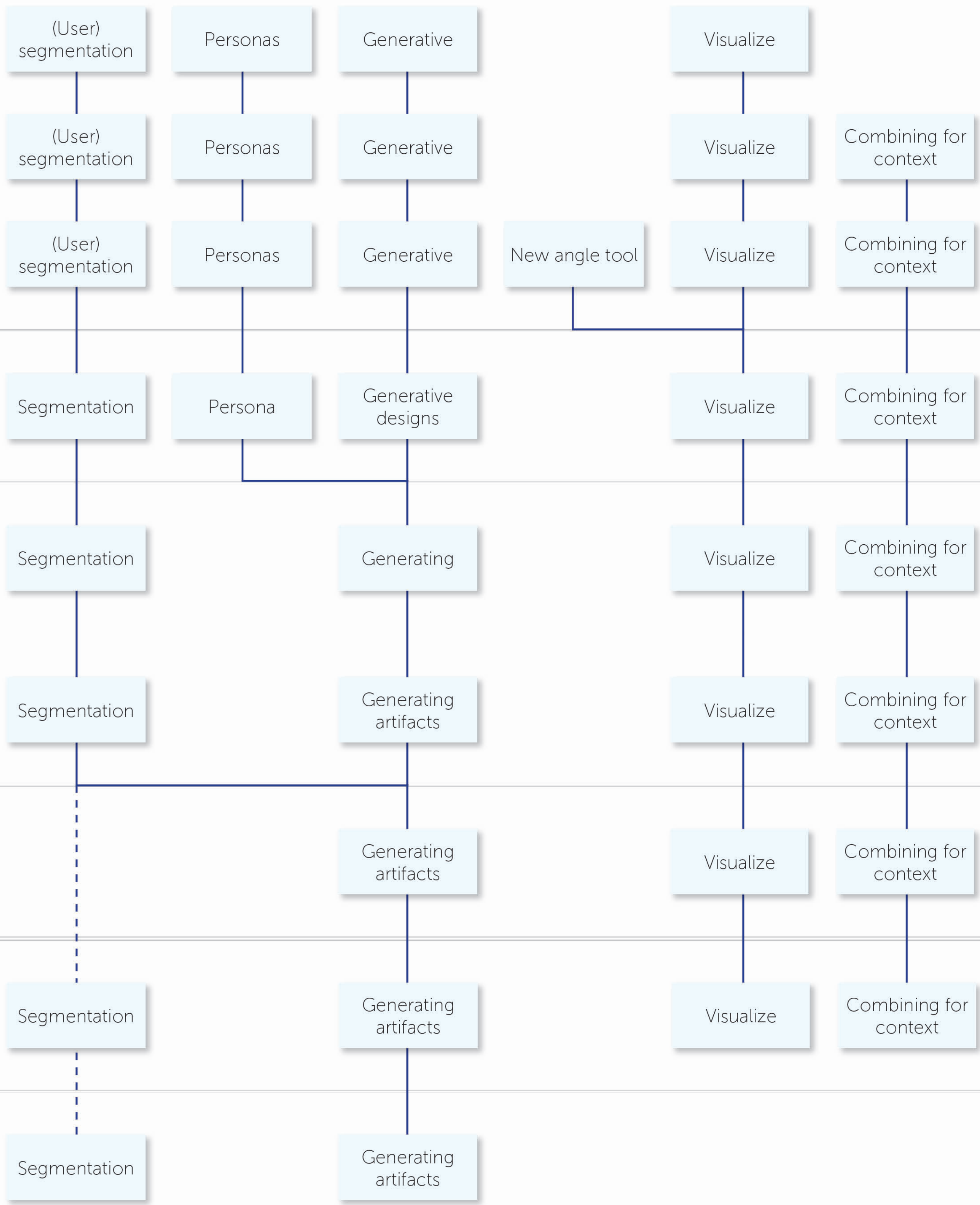
(User) segmentation
Personas
Generative
Visualize
(User) segmentation
Personas
Generative
Visualize
Combining for context
(User) segmentation
Personas
Generative
New angle tool
Visualize
Combining for context
Segmentation
Persona
Generative designs
Visualize
Combining for context
Segmentation
Generating
Visualize
Combining for context
Segmentation
Generating artifacts
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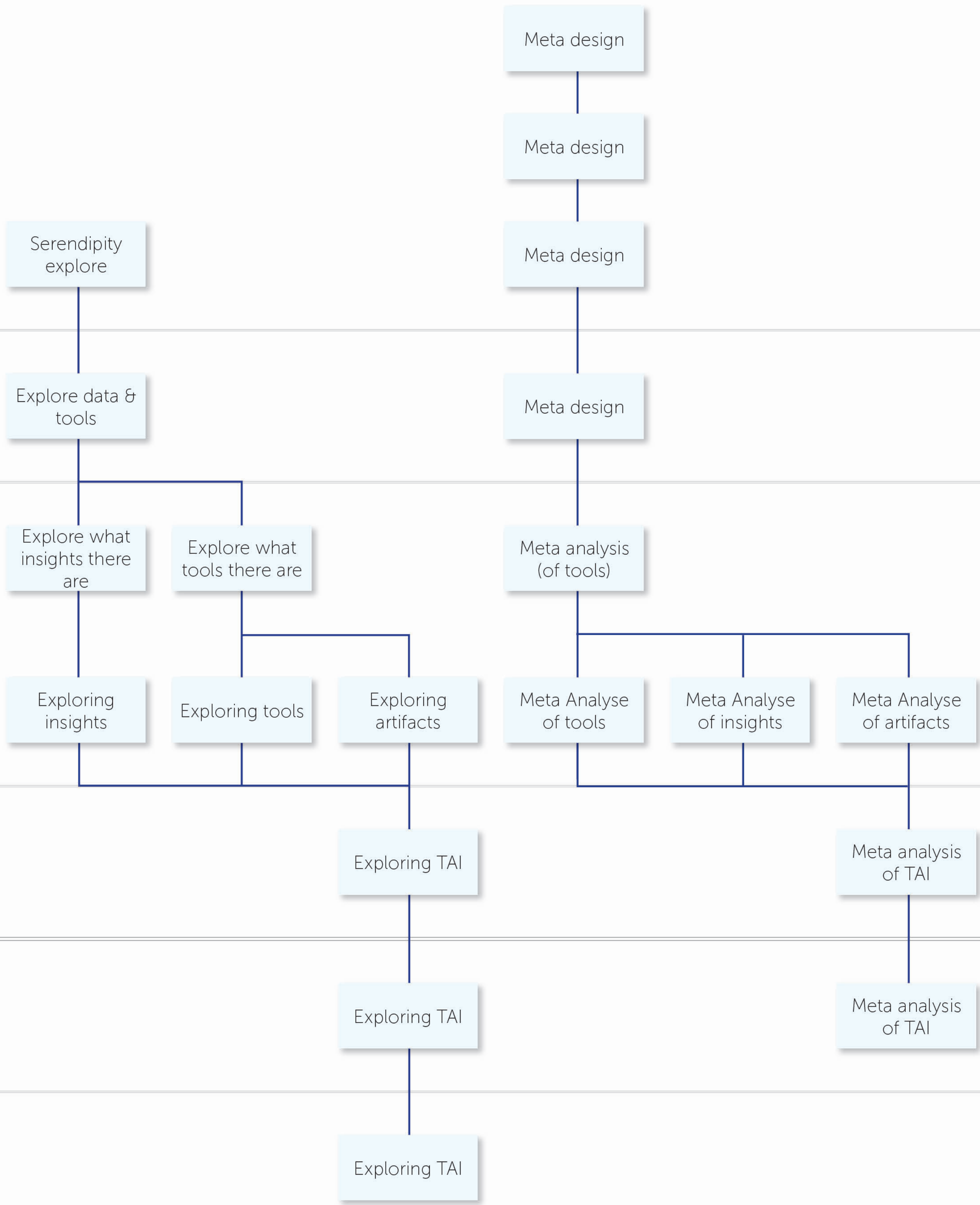
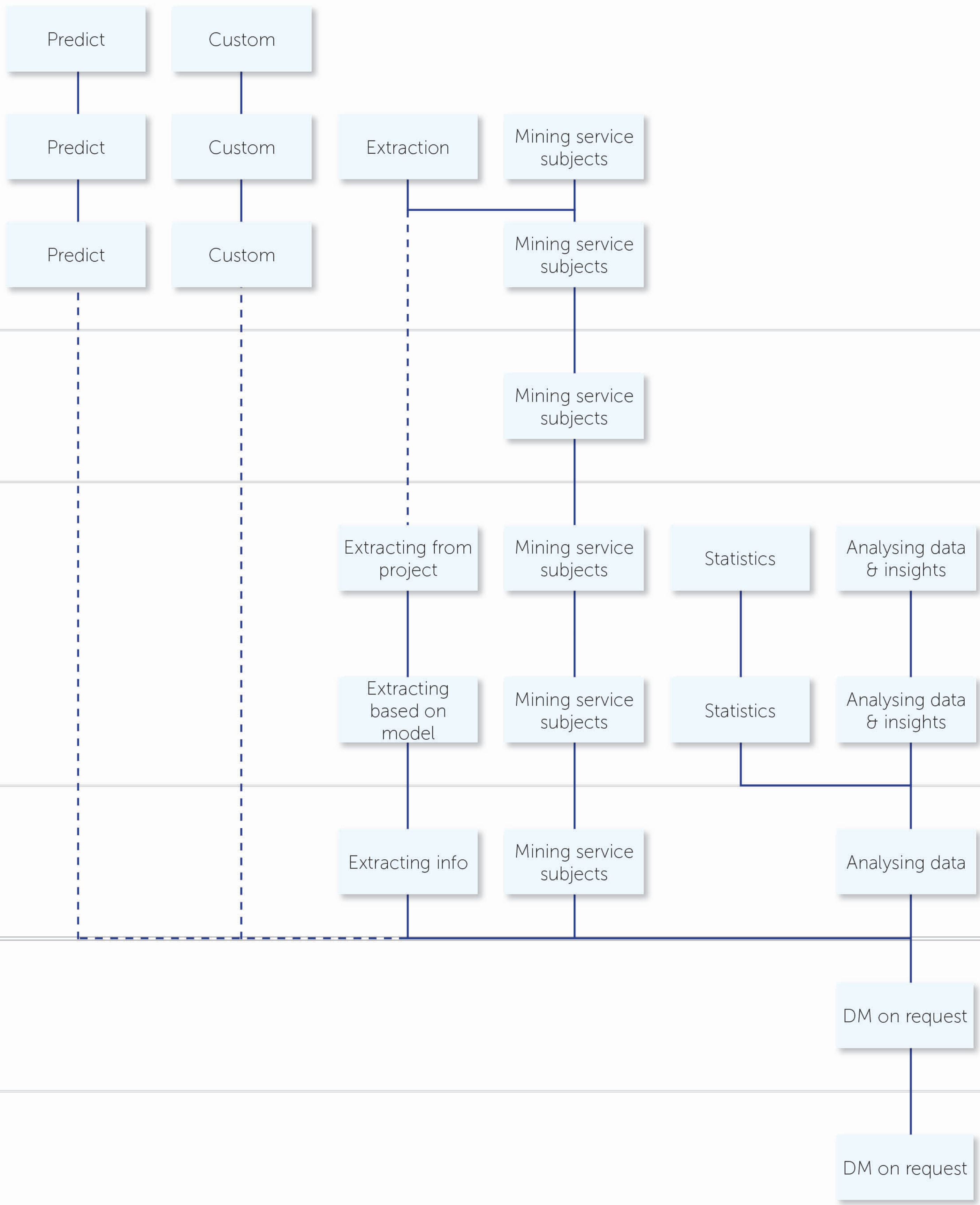
Combining for context
Segmentation
Generating artifacts

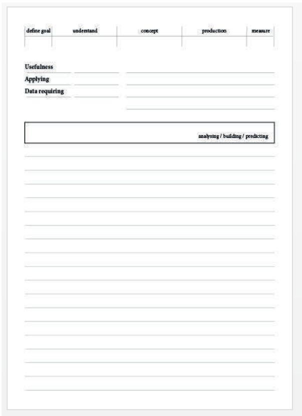

Meta design
Meta design
Serendipity explore
Meta design
Explore data & tools
Meta design
Explore what insights there are
Explore what tools there are
Meta analysis (of tools)
Exploring insights
Exploring tools
Exploring artifacts
Meta Analyse of tools
Meta Analyse of insights
Meta Analyse of artifacts
Exploring TAI
Meta analysis of TAI
Exploring TAI
Meta analysis of TAI
Exploring TAI



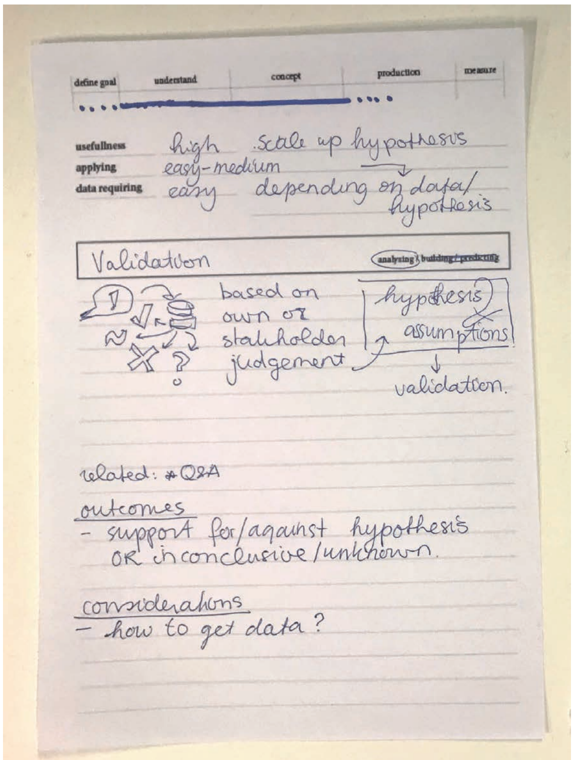
Predict
Custom
Predict
Custom
Extraction
Mining service subjects
Predict
Custom
Mining service subjects
Mining service subjects
Extracting from project
Mining service subjects
Statistics
Analysing data & insights
Extracting based on model
Mining service subjects
Statistics
Analysing data & insights
Extracting info
Mining service subjects
Analysing data
DM on request
DM on request

A4. Process visuals

The visuals discussed in *Research process* (Chapter 4) are listed non-chronologically in this section.



(a) Digital version



(b) Printed and used version

Figure A4.2. The first method card contained attributes from both design and data mining.

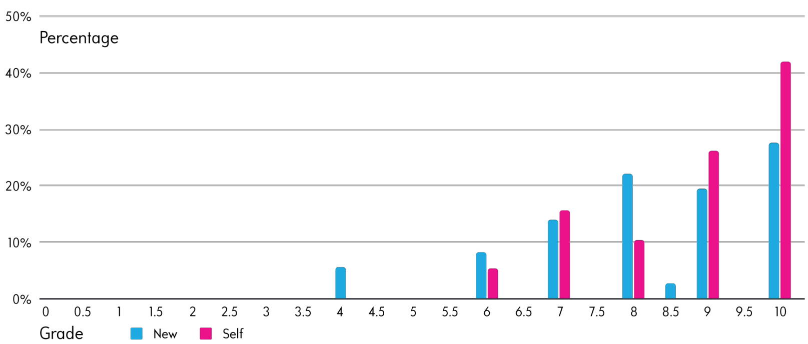


Figure A4.3. Grades given to own top five (pink) and new data science (blue) outputs of the methods (non-significantly different).

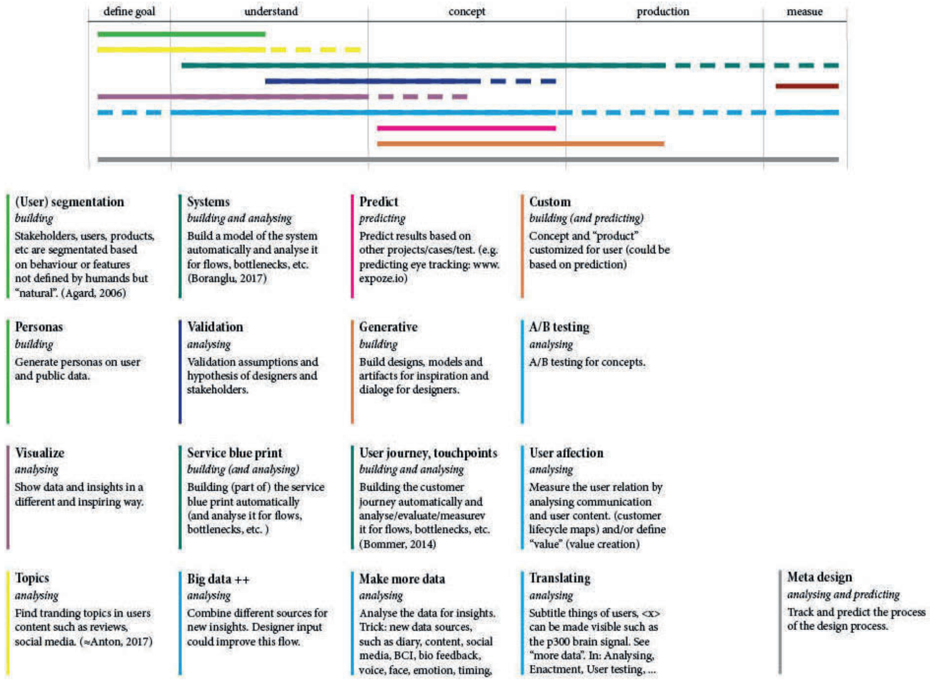
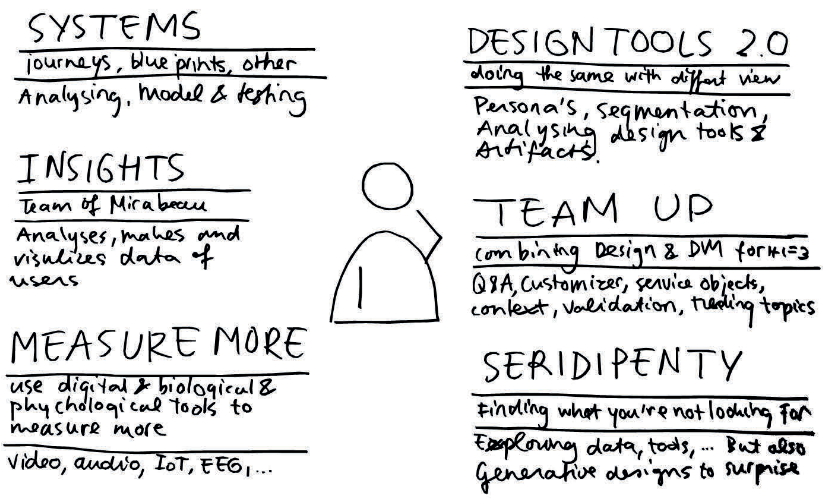
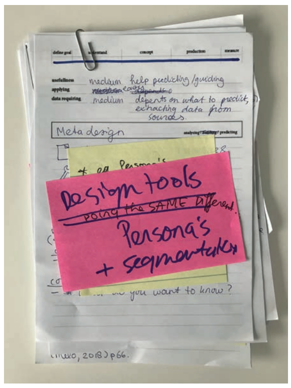


Figure A4.4. One of the first overviews of the methods. The methods are in relation to the design process, which is in this case labelled as "the way we work" of Mirabeau.

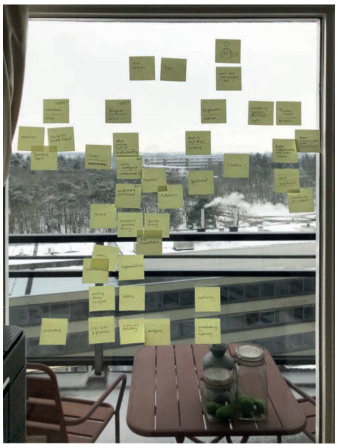




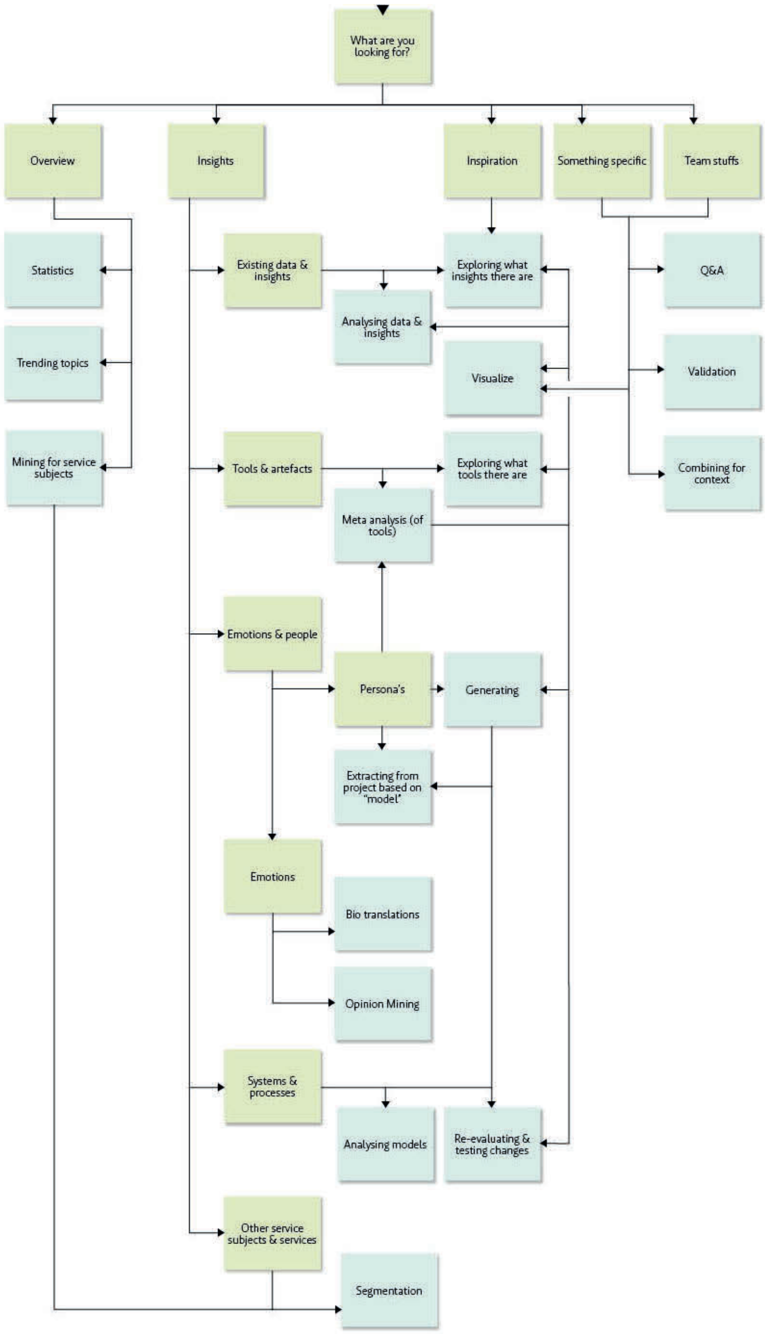
(b) After session

(a) Definined categories

Figure A4.5. The six categories were based on the existing methods.



(a) Brainstorm results from perspective of the user: "What are you looking for?".



(b) Overview of needs of designers (green) that result in methods (blue)

Figure A4.6. This brainstorm that started with the user.

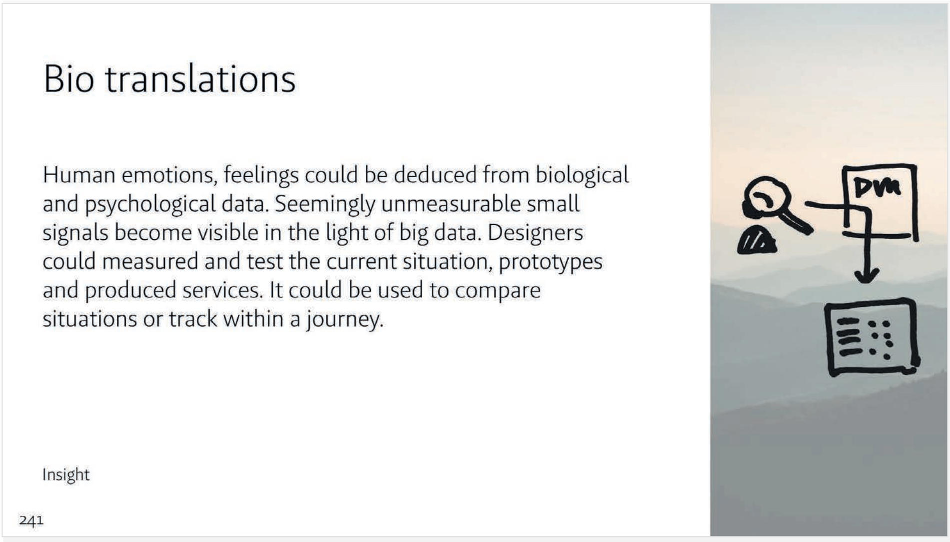
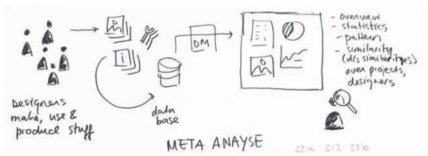
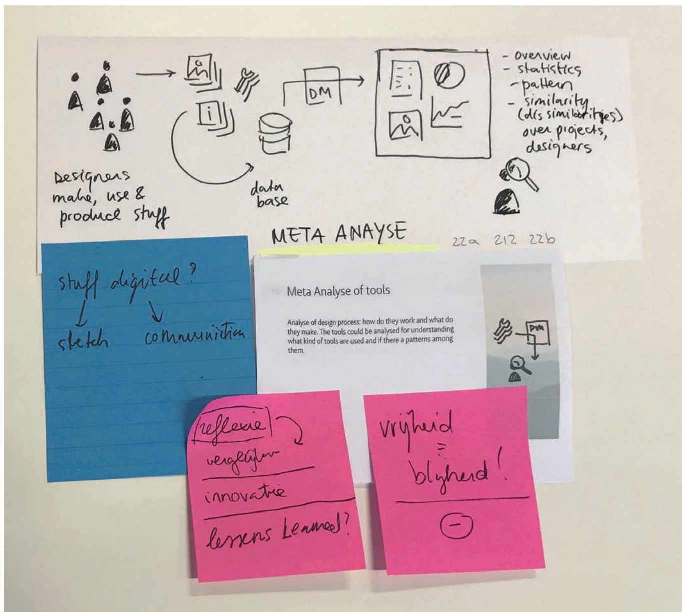


Figure A4.7. The minimal method card.



(a) The example sketch shows how the data is collected and processed for the meta design method.



(b) Feedback from both designers are the blue and pink notes.

Figure A4.8. Method cards, sketches and feedback sticky notes.

Introduction Facilitator welcomes participant and tells course of events.

Warming up Provide context and clarify the concept of 'output'

1) Participant writes down the personal top five most used design methods on notes. An example is given by the facilitator. The results are shared.
2) The facilitator introduces the PTC case. The participant creates fake outputs on A5 paper for the own top methods. The example output is a person that tells personal preferences about sitting in a bus during. The participant has limited time and places the notes with method name on the A5 paper sheet. The output of the participant are discussed afterwards.

Evaluation How and why data-driven outputs could be used

1) The outputs of a data-driven method are presented and discussed per round. The output group is explained shortly and the participant is asked to place them in order of usefulness. Then an interview follows about how and why (not) use the output. The outputs could be altered.
2) At the end of the round selects the participant which outputs would be used in the fake case by placing them by the own methods.

Close session Facilitator thanks participant and ask how the workshop went.

Figure A4.9. The global setup of the pilot workshop.

Introduction Facilitator welcomes participants and tells course of events.

Warming up Provide context and clarify the concept of 'output'

1) Participants write down the their own top five most used design methods on notes. An example is given by the facilitator. The participants share their results.
2) The facilitator introduces the PTC case. The participants create fake outputs on A5 paper for the own top methods. The example output is a person that tells personal preferences about sitting in a bus. The participants have limited time and place the notes with method name on the A5 paper sheet. The outputs of the participant are discussed afterwards.
3) The participants receiver mini sticky notes to write a grade (0-10) to their outputs. The grade symbolises how likely they would use it in their next 'standard' project. The outputs are moved to the other end of the table, but still visible for each participant.

Evaluation How and why data-driven outputs could be used

1) The outputs of a data-driven method are presented and discussed per round. The output group is explained shortly and each participant receives an individual set of outputs. Then the interview follows, where the facilitator stimulates the participants to discuss their visions among themselves. The outputs could be altered.
2) The participants also place grades on the data-driven outputs. All outputs including own outputs from the warming up are distributed over the table. Updating the grades is allowed.

Close session Facilitator thanks participants and ask how the workshop went.

Figure A4.10. The global setup of the workshops (differences with pilot are blue).

Figure A4.11. Design-driven data pilot Workshop

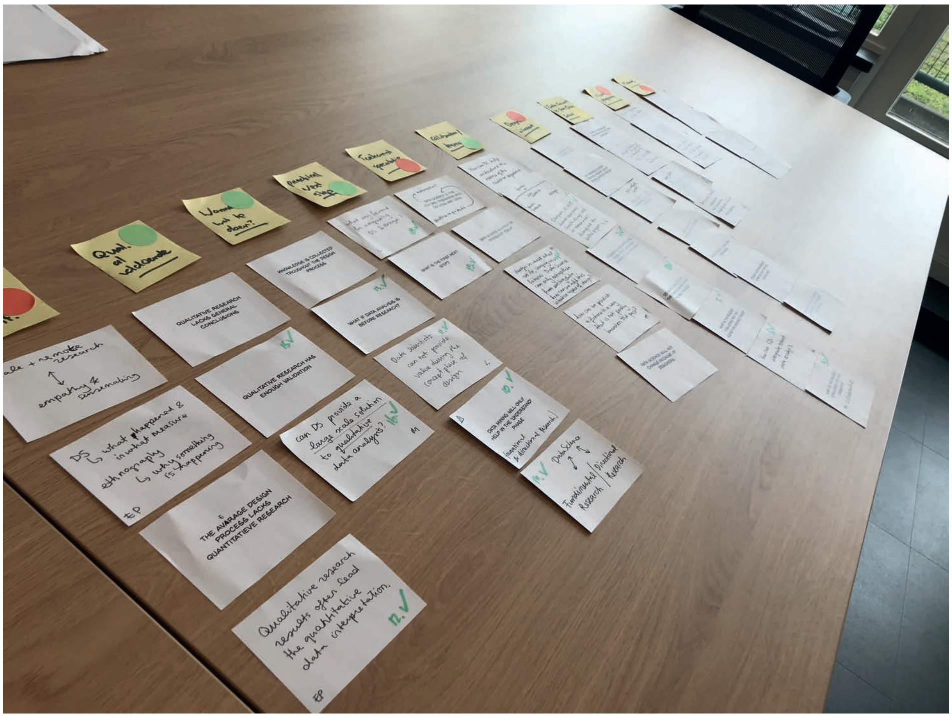


Figure A4.12. Organising the panel discussions

Group	Priority		Statements discussed
Data science for data scientists	🟡	1	Data science is like magic; you need a specialist to do it.
		2	Designers should understand -and to a certain extend be able to do- data science.
Collaboration & teams	🟢	3	A team should consist of data science, user research and design.
		4	Designers, Data scientists and human researchers should always work in mixed teams throughout the entire project.
		5	What is the biggest challenge for the agency or in-house team?
		6	How can service designer integrate robust data analysis?
		7	How are designers, researchers, developers and data scientist different?
		8	Designers need to do their own research for the best results.
		9	What is the biggest challenge for the designer in collaboration?
When doing what?	🟢	10	Data mining will only help in the 'understand' phase.
		11	Data scientist can not provide value during the concept phase of design.
		13	What if data analysis is before research?
		14	How is data science related to foundational vs. directional research?
Qualitative is enough	🟢	15	Qualitative research has enough validation.
		16	Can data science provide a large scale solution to qualitative data analysis?
Future speculation	🔴	12	Qualitative research results often lead the quantitative data interpretation.
		17a	Design is about what can be, imaging new futures.
		b	Data science can only extrapolate from existing data.
		c	How can we add this intuitive aspect of design?
Practical next steps	🟢	18	What way forward for integrating data science and design?
		19	What is the first next step?
Qualitative versus quantitative	🟡		-
Design inherent	🔴		-
Client perspective	🔴		-
Methods	🔴		-

Priorities: High 🟢 , Medium 🟡 and Low 🔴.

Figure A4.13. Topics and statements of the panel interview

A5. Overviews of the methods

The methods were regularly scored and updated. *Ideation* (Section 4.2) describes this process on page 33. The score data was useful to compare the concepts to each other, refinement and apply criteria.

The following colours are used to indicate the method categories: ● User research, ● Systems, ● Serendipity and ● Collaboration (Chapter 6).

	Main purpose				**Design process**						
	Ovr	Ins	Msr	Col	Pre	Und	Def	Ide	Tst	Imp	Mnt
Opinion mining ●	7	1	7	1	7	7	6	1	7	2	6
Bio translations ●	7	1	7	1	1	7	1	1	7	2	3
Systems ●	7	3	6	4	7	7	7	3	6	7	7
Explore TAI ●	7	7	2	2	3	6	6	7	4	1	1
Meta analyse ●	6	4	1	1	6	7	6	6	7	1	2
Generating artifacts ●	7	6	4	1	4	6	6	7	5	4	2
Segmentation ●	7	6	5	1	7	7	7	5	4	6	7
DM on request ●	7	2	4	7	7	7	6	2	5	7	6
Q&A ●	7	1	7	7	4	7	7	4	5	1	3
Combining for context ●	7	3	1	7	6	7	6	4	1	3	1
Visualise ●	5	6	2	7	5	6	7	6	2	2	1

	Data subject			**Technical level** is low			**Qual-Quan**	
	User	Project	Meta	Underst	Build	Maturity	Qual	Quan
Opinion mining	7	6	1	7	6	6	7	7
Bio translations	7	4	1	7	4	4	7	7
Systems	5	7	1	2	1	1	2	7
Explore TAI	4	6	7	7	7	7	7	4
Meta analyse	7	6	4	7	6	6	5	5
Generating artifacts	7	7	5	7	5	5	5	5
Segmentation	6	7	2	5	7	5	3	7
DM on request	6	7	4	4	6	4	5	6
Q&A	7	7	2	7	7	7	5	7
Combining for context	6	7	4	6	6	6	4	4
Visualise	6	7	7	7	7	7	4	7

Main purpose

Ovr	Ins	Msr	Col
Overview & Insights	Inspiration	Measure	Collaborating

Design process phases from the HHD service design process model (Section 2.2.1)

Pre	Und	Def	Ide	Tst	Imp	Mnt
Prepare	Understand	Define	Ideate	Test	Implement	Maintain

Data subject

User	Project	Meta
User-related data	Project-related data	Data about designers and their way of working

Technical level

Underst	Build	Maturity
Easy to understand	Easy to build	Easy to embed in the organisation

Qual-Quan

Qual	Quan
Qualitative	Quantitative

Scores

Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
1	2	3	4	5	6	7

Figure A5.2. The methods are scored on attributes, such as main purpose and fit to the design process.

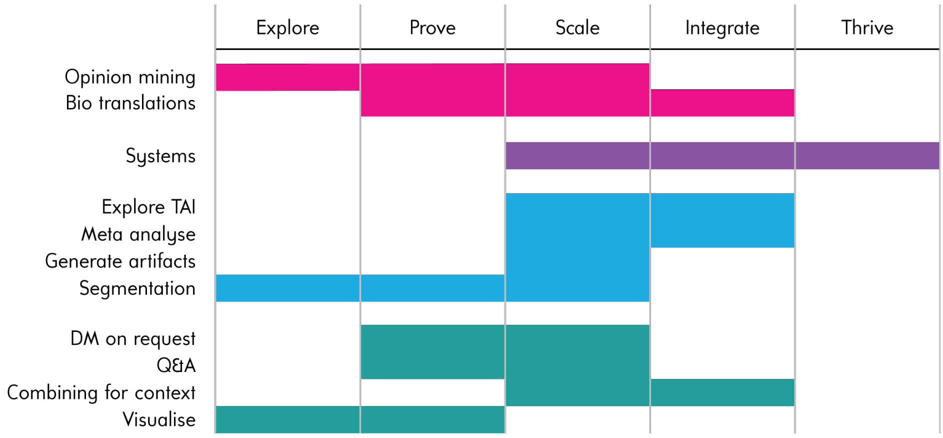


Figure A5.3. Recommended starting phases for the methods compared with the maturity model as defined in *Maturity model* (Section 5.2.1) and Appendix A1.

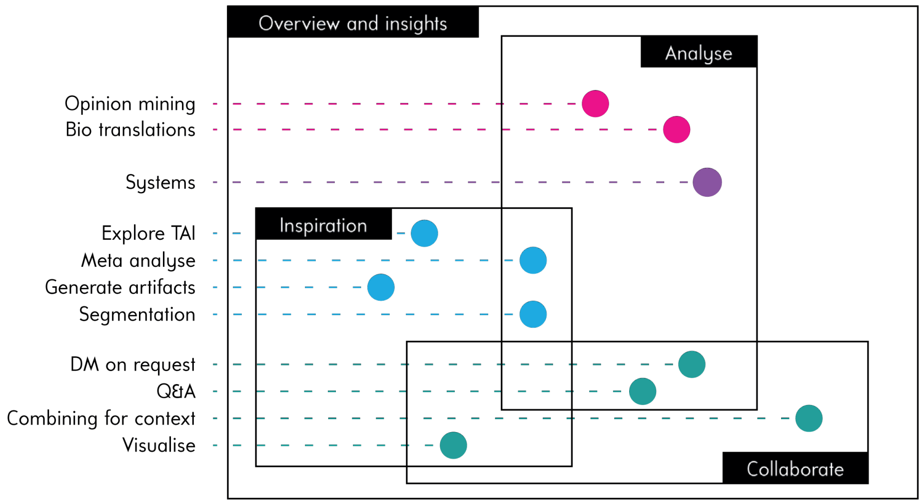


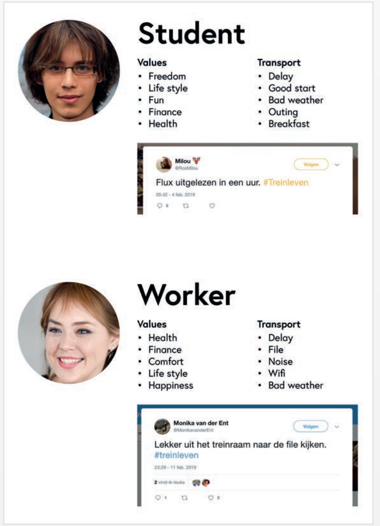
Figure A5.4. The main purposes of the methods are overview & insights. analyse. inspiration and collaboration.

A6. Persona benefits

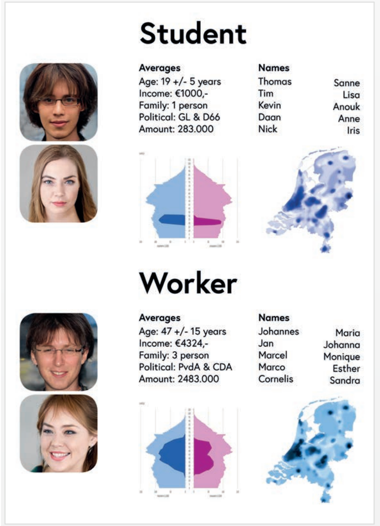
Ranked benefits of personas by Miaskiewicz and Kozar (2011) supplemented with possibilities for machine support, such as automation and providing quantities.

nr	Benefit name	Benefit description (Miaskiewicz & Kozar, 2011)	Machine aids benefit directly
1	Audience focus	Focus product development on users/customers and their goals (rather than the specific limitations or opportunities presented by technology)	no
2	Product requirements prioritisation	Prioritise product requirements and help to determine if the right problems are being solved	no
3	Audience prioritisation	Prioritise audiences and bring about a focus on the most important audience(s)	yes, provide quantities
4	Challenge assumptions	Bring to the surface and challenge long-standing (and often incorrect) organisational assumptions about the users/customers	yes, provide different source to the table
5	Prevention of self-referential design	Help individuals realise how the users/customers are different from themselves	yes, provide different source to the table
6	Decision guide	Are the basis for product design decisions by providing a clear picture of customer needs, and the context/environment for these needs	no
7	Agreement catalyst	Aid in achieving agreement on product definition decisions by clarifying the user/customer goals to varied stakeholders and interests	no
8	Engagement and unification	Engage, unify, and educate individuals who are not close to the users or the user research (such as potential investors, product marketers, or engineers) by creating a clear picture of the product or service	no
9	Empathy creation	Create an understanding of and emotional identification with the users/customers	no
10	Innovative thinking	Stimulate innovative thinking that produces new and better solutions that meet the user goals	no
11	Team collaboration	Foster collaboration among team members from different disciplines through a clear understanding of the customers/users	yes, provide different source to the table
12	Communication aid	Through the shared knowledge of an archetype, assist in communicating within and across teams and stakeholders	no
13	Problem scope definition	Help with defining the scope of a problem that needs to be solved	yes, provide quantities
14	Evaluation guide	Guide the evaluation of product definition decisions	yes, provide quantities
15	Organisation of research data	Assist in organising and utilising research findings about users/customers by structuring research data in a more vivid form than raw data	yes, automation
16	Articulate stakeholders' vision	Help to articulate the product vision and target market strategies of executives and other stakeholders	no
17	Improved usability	Aid in designing more usable products because the goals and the needs of the users/customers are understood	no
18	Product offerings	Can be used by a business to determine what types of products/services to offer and highlight new business opportunities	yes, provide quantities
19	Product evaluation	Can be used to evaluate existing products and their strengths and weaknesses	yes, provide quantities
20	Intuitiveness	Can be used by specialists and non-specialists because individuals intuitively understand stories and how characters work	no
21	Product marketing	Through the use of marketing materials, can be used to tell a compelling story that helps to convince potential customers that their needs and goals are understood	no
22	Reuse of research data	Allow for reuse of user research data for products in the same domain with similar âftŸtypes' of users/customers	yes, summarisation and new insights

A7. Method variation cards for the workshops

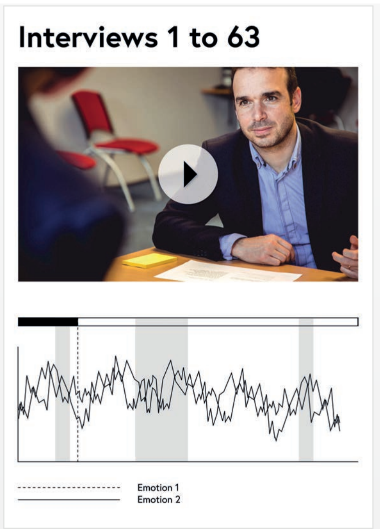


Persona (Section 6.5.3)
Value oriented persona. Profile pictures from (Karras et al., 2019) and tweets from (Milou, 2019; van der Ent, 2019).

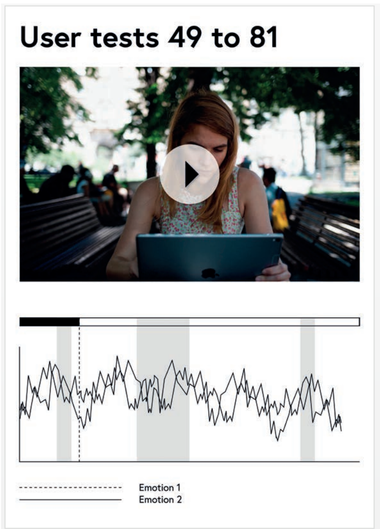


Persona (Section 6.5.3)
Demographic persona. Profile pictures from (Karras et al., 2019) and infographics based on (CBS, 2018; Spoon, 2009).

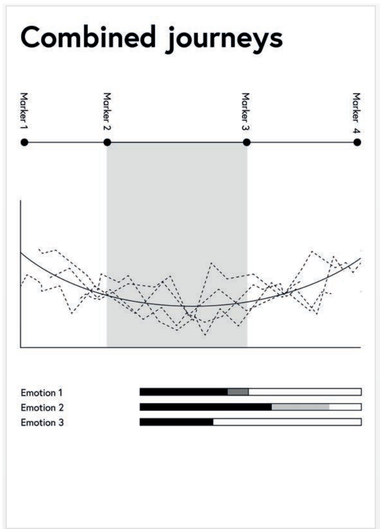
Bio translations (Section 6.3.2)
The analysed video of a single journey, with emotions tracked and time periods highlighted. Photo by Nylind (2014).



Bio translations (Section 6.3.2)
The analysed video of an inter-view, with emotions tracked and time periods highlighted. Photo by Buguet (2018).



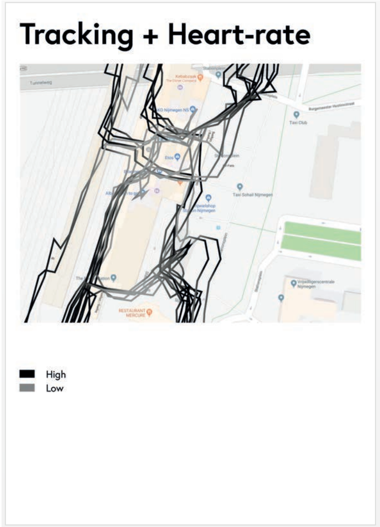
Bio translations (Section 6.3.2)
The analysed video of a user test, with emotions tracked and time periods highlighted. Photo by Vladimirov (2019).



Bio translations (Section 6.3.2)
The analysis of emotions during multiple journey combined in one visual graph.

Bio translations (Section 6.3.2)

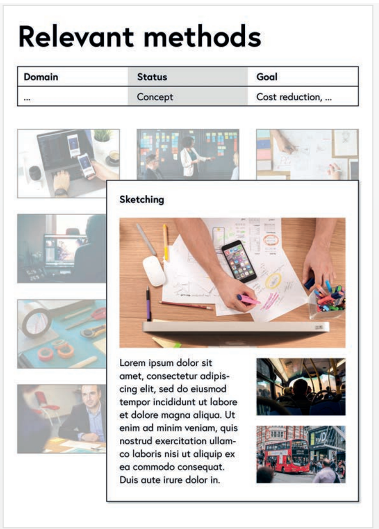
GPS tracking on a map without hart-rate. Map from www.google.com/maps.



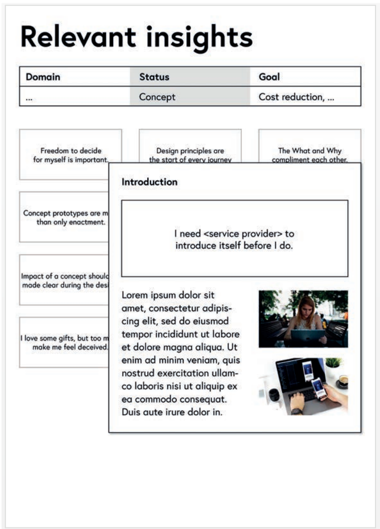
Bio translations (Section 6.3.2)

GPS tracking on a map with hart-rate. Map from www.google.com/maps.

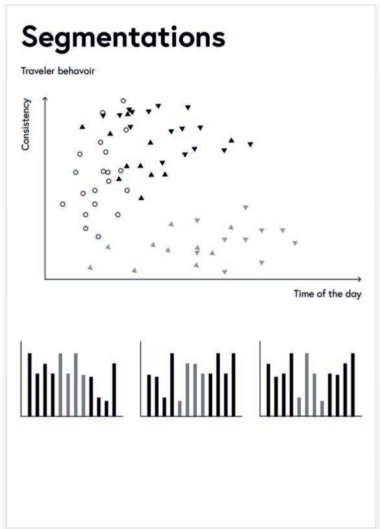
Explore Tools, Artifacts and Insights (Section 6.5.1)
The related projects explorer. Nine photos from unsplash.com[1].



Explore Tools, Artifacts and Insights (Section 6.5.1)
The relevant methods explorer. Nine photos from unsplash.com[2].

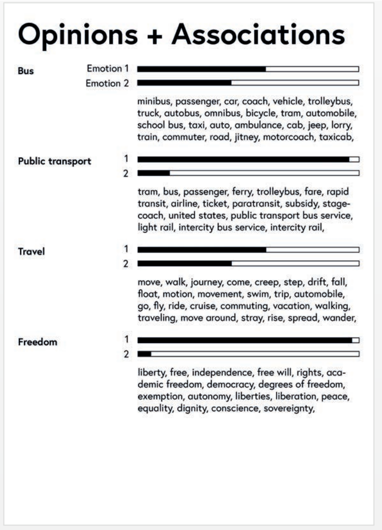


Explore Tools, Artifacts and Insights (Section 6.5.1)
The relevant insights explorer. Two photos from unsplash.com[3].

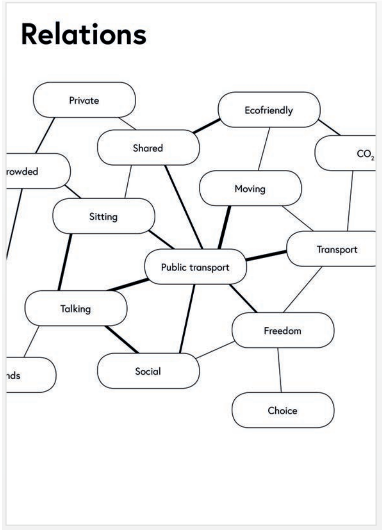


Segmentation (Section 6.5.4)

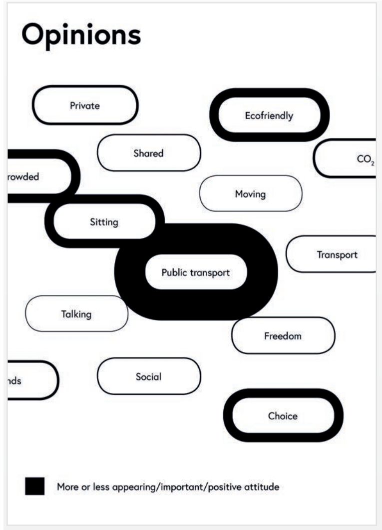
Segmentations in a graph with subplots for each segment.



Opinion mining (Section 6.3.1) Mined words with emotion scores and associations. Associations are generated with `related-words.org`.



Opinion mining (Section 6.3.1) Network of mined relations between words with their strengths.



Opinion mining (Section 6.3.1) Word-cloud variation with frequency or sentiment strength as size.

[1] By P. Casals, A. Lin, K. Maksim, M. Ceralde, B. Day, J. Chng, D. Abadia, D. Nepriakhina and J. Buguet.
[2] By J. Buguet, D. Korpai, G. Carstens-Peters, J. Szczepanska, J. Chng, P. Casals, Rawpixel (twice), W. Iven.
[3] By S. Vladimirov and D. Korpai.

Appendix B

Glossary

Actual journey
The experienced customer journey in the real world that will lead to 'de facto' model. Antonym of Expected journey. (p. 64)

Artificial neural network
Machine learning technique that learns by adjusting weights of connections in a graph of neutrons. (p. 58)

Clickstream
Click sequence of a user navigating trough one or more websites. (p. 79)

Customer journey map
Visual representation of the timeline of events from perspective of the customer (customer journey). (p. 64)

Data
Factual statements or output. (p. 44)

Design system
Collection of design elements and standards for guiding and embodiment of the brand. (p. 74)

Deterministic model
Model that produces a single outcome and is consistent in the same condition. Antonym of Probabilistic model. (p. 66)

Directional research
Design/user research with a small scope to answer a specific question of hypothesis. Antonym of Foundational research. (p. 44)

Expected journey
Planned or theoretical customer journey that will lead to 'de jure' model. Antonym of Actual journey. (p. 64)

Explainable Artificial Intelligence (XAI)
The clarification and communication about decisions and conclusions of AI systems. (p. 46)

Factor analysis
A statistical method that finds correlations with observed variables and unobserved variables called factors. (p. 55)

Foundational research
Design/ethnographic research to gain understanding of a bigger and profound picture. Antonym of Directional research. (p. 44)

Generative adversarial networks (GAN)
Artificial neural networks are trained to respectively generate and evaluate new data based on the original data. (p. 73)

K-means clustering
Clustering into *k* groups by selecting the nearest mean for a new item. (p. 79)

Key performance indicator (KPI)
Key performance indicator to measure business objectives. (p. 58)

Hierarchical clustering
Clustering by defining a three-like hierarchy of clusters. (p. 79)

Information
Human representation of a collection of data. (p. 44)

Insight
Understanding from observation, information or other design/user research. (p. 72)

Labelled data
Data where the data-points have tags called labels, which can be seen as the correct answers. (p. 58)

Markov model
Model that represents states and predicts the (best) next state based on partially or fully observable systems. (p. 65)

Method triangulation
The combination of methods projecting the same phenomenon via different angles. (p. 45)

Neural network
See Artificial neural network. (p. 58)

Onboarding package
Collection of information for kickstarting or onboarding a project. (p. 70)

Opinion mining
Subfield of data mining and focusses on extracting and analysing opinions. Also called Sentiment analysis. (p. 54)

Probabilistic model
Model that produces a probability distribution as a solution. Antonym of Deterministic model. (p. 66)

Process mining
Field similar to data mining that extracts process-related information from event-logs. (p. 63)

User research
Methodology for understanding the behaviors, needs and motivations of users (and stakeholders). Sometimes called design research. (p. 12)

User story
Description of feature(s) and requirements of a system from point of a user. (p. 14)

SCRUM
Agile framework for software development with time-boxed iterations and time-boxed stand-up meetings. (p. 13)

Sentiment analysis
See Opinion mining. (p. 54)

Supervised learning
Learning from labelled data, aka learning with predefined correct answers to learn from. Antonym of Unsupervised learning. (p. 79)

Sprint
A time-boxed SCRUM iteration where activities defined at the start. (p. 70)

TAI
Tools, artifacts and insights made by/for (service) designers. (p. 67)

Training dataset
Part of the dataset that is preserved for learning the solution. The other part is for testing. (p. 20)

Test dataset
Part of the dataset that is preserved for testing if the models has the right solution. The other part is for training. (p. 20)

Unsupervised learning
Learning from data without labels, aka learning without predefined correct answers to learn from. Antonym of Supervised learning. (p. 79)

Visual saliency
Subjective quality of visual perceived items and if they grab the attention. (p. 74)

Appendix C

References

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