data design innovation

The integration of data science in design innovation at digital consulting firms.

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Master thesis

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Foreword

The last seven months have been a great experience - graduating from the Master Strategic Product Design that I enjoyed from the first moment. Considering I have written this graduation thesis practically next to my bed, the journey could have been much worse if it were not for a wonderful group of people.

To my supervisor team, Barend and Rebecca, thank you for your tremendous support. From the first moment, I only had two possible supervisors in mind and I am grateful that I got the opportunity to learn from you. Rebecca, thank you for your coaching, from my first moment at the Master (the SPD project) all the way to my last. Your sharp coaching and critical but always positive attitude have inspired me throughout this entire Master. Barend, thank you for joining me on this great journey. You guided me throughout this thesis and have pulled me through quite some chaotic times. I always looked forward to meeting with you and enjoyed your enthusiasm and wisdom in the design field. What a great team you both are.

Maik, my company mentor. Thank you for your endless dedication to this project. Being the first one in line between a stubborn critical researcher and the company is not an easy job. You have proved more than worthy - your energy and knowledge had a great impact on the thesis. I also want to thank some individuals at the firm Liset, as the second mentor, sending me text messages even after a late co-creation session. Lotte supported me after work hours to bring the facilitation to the next level. Bas for your exciting perspectives on design and innovation and Theo for putting this crew together. I wanted to thank Daniel and Noor for your willingness to share information and enthusiasm from the strategy team. From the data science team, Cornelis, thank you for acting as the bridge between the data science team and participating in many events. Last, Martijn, your interesting perspectives delivered a great contribution to the thesis. You have built a great group of people together, and I am sure it is only getting bigger, better and bolder. I am grateful that I had the opportunity to perform the project with such a dynamic and talented group of people.

Last, I want to thank my friends, two roommates and family for their endless support. To my parents, I think of all people, you have contributed the most to this thesis. Forming me from this annoying little creature into something that was suddenly writing his thesis about data science and design innovation, wait, what? A special thanks must be given to my partner for supporting this idiotic and complicated mind. Thank you for your enthusiasm, endless conversations and valuable input.

Abstract

For organisations, the capability to exploit data for innovation efforts has already become imperative to their survival in an ever more competitive market. However, many organisations are currently still struggling with how, where and when to use data science for innovative purposes. The consulting industry is a significant driver for the development of such knowledge for organisations. In addition, in the past decades, consultants have adopted design thinking as a practice to support client's innovation efforts.

The digital consultant firm (DCF) provides professional services to connect the enterprises' business strategy with implementation across digital fields, including design innovation and data science. Based on initial research, the collaboration between data scientists and designers is found to be an issue. This is problematic, considering the importance of data for their enterprise client's innovation efforts. Is the DCF able to achieve synergy between data science and its current design innovation approach, or is polarity simple to large? This thesis aims to explore and design practical support for digital consulting firms to integrate data science in their current design innovation approach. This is done by answering two research questions: (1) how can digital consulting firms integrate data science in design innovation? (2) how can this data-design integration be facilitated in digital consulting firms?

To answer these questions, a design science research approach in the information systems is taken. Based on empirical research, including two collaborative workshops between the DCF's data scientist and designers, two significant findings are drafted. First, data-informed design is a viable opportunity for the DCF to use data science in design innovation client projects. However, a lack of cross-functional learning and a lack of cross-functional decision-making constrain the DCF from exploiting this opportunity. In addition to integrating the two teams, this results in missed revenue and a risk of high overhead costs.

The firm is argued to facilitate the data-design integration by using a person-to-person knowledge strategy to tackle this challenge. The firm should institutionalise an internal alignment meeting before proposals are shared with the client. This meeting aims to support the data and design team's decision-makers with drafting viable proposals, increase the number of collaborative projects. In addition, a framework for interdisciplinary decision making is designed to support the person-to-person knowledge transfer to the decision-makers.

Using a newly proposed method, job prototyping, a new role in the organisation is iteratively developed together with employees. The final concept is validation during an actual internal alignment meeting with the DCF's data and design decision-makers and a potential job-holder. The firm should create a new position in the organisation, 'the data design lead'. This person serves as a hinge between the two teams and aims to transfer his knowledge by acting as a sparring partner during the internal alignment meeting. In addition, a set of guidelines are designed to increase the impact of this new role on the data-design integration. The research findings provide a strategic and viable direction for digital consulting firms to facilitate data science integration in their design innovation process.

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Glossary

Digital consulting firm (DCF): firm that provides professional services aiming to connect clients' business strategy to implementation across different digital fields (Peshev, 2019).

Data: discrete, objective facts or observations, which are unorganised and unprocessed and do not convey any specific meaning" (Rowley, 2007, p. 165)
Big data: describes large volumes of high velocity, complex and variable data that require advanced techniques and technologies to enable the capture, storage, distribution, management, and analysis of the information. (TechAmerica Foundation's Federal Big Data Commission, 2012).

(In this thesis, the term **data** generally refers to **big data**)

Data science: a set of fundamental principles that guide the extraction of knowledge from data (Provost & Fawcett, 2013).

Design innovation: the performance of design practises with the intend to influence an organisation's nnovation efforts.

Data driven innovation: the use of data and analytics to improve or foster new products, processes and organisational methods (OECD, 2015).

Data-driven design innovation (DDI): the utilisation of (big) data by data scientists (and thus performing data science) for data-driven decision making to drive an organization's currently design-driven innovation efforts.
e.g. DDI knowledge: this is a broad term referring to all knowledge regarding data-driven innovation.

Data-driven decision making (DDD) the practice of basing decisions on the analysis of data, rather than purely on intuition." (Provost and Fawcett, 2013).

Integration: the quality of the state of collaboration amongst departments required to achieve unity of effort by the demands of the environment (Lawrence and Lorsch, 1967, p. 11).

Knowledge: the information which professionals acquire through experience and training, together with the judgement which they develop over time which enables them to deploy that information effectively in order to deliver client service.' (Morris and Empson, 1998).

Data team: DCF's data science team
(data science team and data team are both used)
Design team: DCF's design team

1. Project Context

This chapter provides the foundation to the context of the thesis. It elaborates on the relevance and the objective of this research on the intersection between data science and design-driven innovation. The chapter further provides this project's design challenge and the approach by which this thesis aims to accomplish that challenge.

Sub chapters

1.1 Project context

The adoption of data has received attention from nearly every aspect of our lives - the generation of data from our devices like smartwatches or watching Netflix. We even have introduced a smart speaker in our home. All designed to generate and collect data. Technology has empowered companies to store, transform and use it to create innovations, rising tech giants like Airbnb, Netflix or Google. According to a recent study by Accenture (figure 1.1), AI has the potential to boost rates of profitability by an average of 38 per cent by 2035 across 16 industries of about US $14 trillion (Purdy et al., 2018).

Data science in innovation
Until recently, companies mainly focussed on the implementation of data science on automation and optimising. However, we have 'entered the golden age of digital innovation' (Fischman et al., 2014). Meaning digital technologies are increasing in impact on companies' management of innovation (Trabucchi, 2019). The most promising applicability ahead could be using data science as a potential source for the innovation of businesses (Verganti et al., 2020). With vast amounts of data now available, companies in almost every industry are focused on exploiting data for competitive advantage (Provost and Fawcett, 2013). A recent study by Cronhol, Goble & Rittgen (2017) even argues that "for businesses, the capability to exploit data in order to develop new services, has already become imperative to their survival in an ever more competitive market". This activity is defined as data-driven innovation, "the use of data and analytics to improve or foster new products, processes and organisational methods" (OECD, 2015).

Data science is defined as a set of fundamental principles that guide the extraction of knowledge from data' (Provost & Fawcett, 2013). For businesses, the importance of using data science is the ability to base decisions on that extracted knowledge. Otherwise referred to as data-driven decision-making (DDD), i.e. "the practice of basing decisions on the analysis of data, rather than purely on intuition." (Provost and Fawcett, 2013).

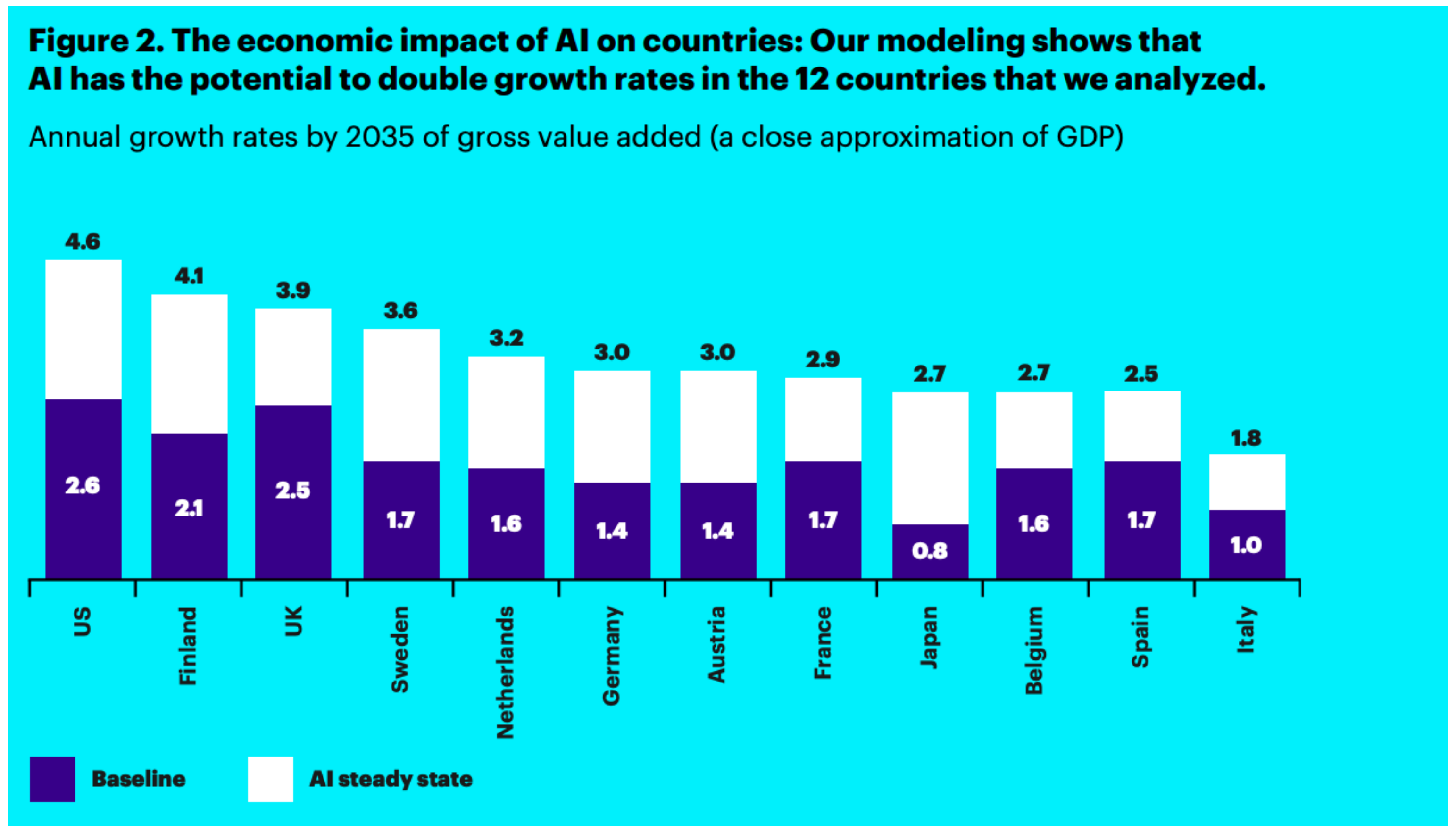


Figure 1.1 - Economic impact of AI on countires (Accenture & Frontier Economics)

"Data is the new oil"
- Humby (2006)

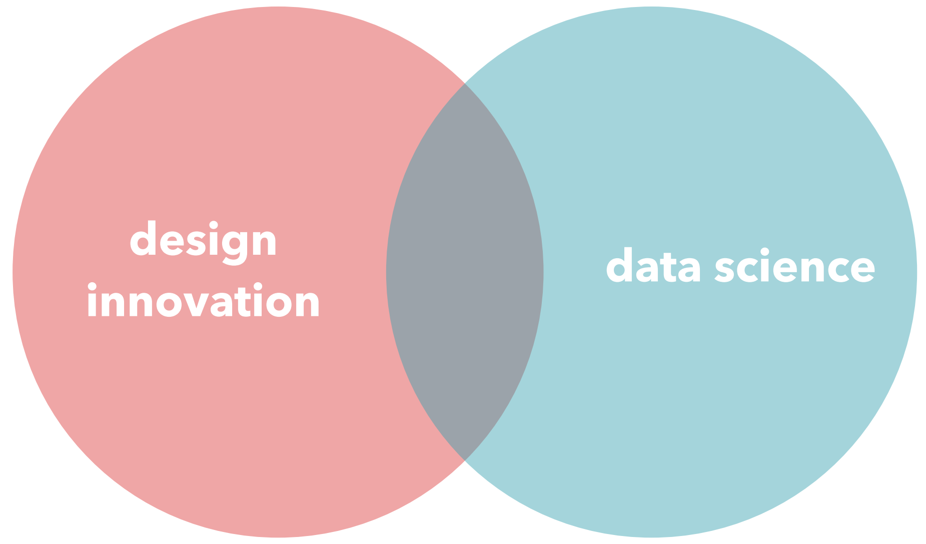


Figure 1.2 - Data-driven design innovation - the intersection between design driven innovation and data science

Design in innovation
Alternatively, in the past decades, design thinking has been widely recognised as a tool to innovate for organisations (e.g. Gruber et al., 2015), differentiate from competitors, and drive business performance (Liedtka, 2015). In McKinsey's recent research, Business value of design (2018), it is found that best design performers increase their revenues and shareholder returns at nearly twice the rate of their industry counterparts (McKinsey, 2018). The increase of this recognition is mainly due to the applicability of design thinking's three core principles, human-centred thinking, iterative working and abductive reasoning, in solving complex business challenges (e.g. Liedtka, 2015; Verganti et al., 2020; Calabretta and Kleinsmann, 2017).

Synergy or polarity?
Questions arise about how data science and design are going to live together during the future of innovation. Although recent scholars have started to research this topic, the foundation of academic literature on this topic is scarce. Verganti et al. (2020) argue that in big-tech driven firms like Airbnb or Alibaba, AI not only incorporates the three essential principles of design thinking but could outperform human-centred innovation by eliminating human-intensive limitations. They suggest that problem-solving will be replaced by computers and design in big- tech-driven firms and will shift its focus to problem finding. The question remains if these conclusions apply to companies that are not big-tech natives. This thesis researches the utilisation of (big) data by data science for data-driven decision making to drive an organisation's current design innovation efforts. This term is now referred to as data design innovation or DDI.

Many organisations are still struggling with how, where and when to use data science for innovative purposes (Duan et al., 2020). The consulting industry is a significant driver for developing knowledge of these organisations (Løwendahl, Revang and Fosstenløkken, 2001) because many significant decisions in a wide range of organisations and sectors are made with the assistance of consultants (Kipping, 2013). Furthermore, as design thinking is widely recognised as a tool to innovate for organisations, the practice of design consulting increases the influences of consulting firms clients' strategies and innovation performance (Calabretta et al., 2013). This trend is recognisable in the consulting industry. A publication by Gartner indicated that digital design and innovation consist more than 50% of the capabilities acquired by consulting firms. These acquisitions allow the firms to bring in human-centred methods, advice on technologies and agile approaches, and focus on user experience to enhance their expertise and design innovation that lead to downstream work (Gartner, 2019). Examples are Deloitte acquisition of design agency Doblin, Accenture's acquisition of Fjord and even the more traditional firms like Bain required design agency FRWD. According to Kolko (2015), these acquisitions argue "that design is becoming table stakes for high-value corporate consulting—an expected part of a portfolio of business services'' (Kolko, 2015., p6). However, the growing impact of data science and the urge for organisations to use data science for innovation raised questions for these consultant's current design innovation approaches. Are consultants able to achieve synergy between data science and the current design innovation approach, or is polarity simple to large? This thesis aims to explore and design support for consulting organisations to integrate data science in their current design innovation approach.

1.1.3 Context - digital consulting firm

This thesis is written in collaboration with a medium-sized (50-255) digital consulting firm (DCF). This section discusses the business relevant problem, based an initial empirical investigation (see chapter 3.1 for more elaboration). Based on interviews with employees, a SWOT (figure 1.3) and a trend analysis (figure 1.4), it is concluded that the DCF has issues integrating its data science and design team. Appendix 1.2 provide a more indepth discussion of the SWOT analysis.

Digital consulting is defined practises that connects clients' business strategy to implementation across different digital fields (Peshev, 2019). The DCF in question provides professional services on; strategic consulting, digital design, data science, paid marketing, email marketing and e-commerce. According to the director this multidisciplinarity allows the firm to offer 'total solution' to client challenges and to 'sell down the line' (ie. sell more projects of other internal expertises).

The DCFs main strategy is growth towards larger enterprises. "A growth strategy is an organization's plan for overcoming current and future challenges to realize its goals for expansion (Gartner, 2021)" based on three drivers; (1) maintain relevance to enterprise clients with its increasing complexity of the challenges, (2) ability to compete in a consulting market that is consolidation (acquisition strategy of large consulting firms and entrance of IT companies) and (3) attracting the right kind of talent. As large enterprises' innovation efforts are becoming essential to be data-driven (Cronhol, Goble & Rittgen, 2017), this strategy raises the questions if DCFs strategy is in line with their current multi-disciplinary design innovation process.

From a strategic point of view, DDI provides both opportunity and a threat. Concluded from the trend analysis, the increasing availability of data, the maturing of data analytics, and the increasing applicability to digital design and innovation (Deloitte 2020), DDI is of increasing importance for enterprises. Despite the potential use of data-driven innovation, this opportunity is currently missed

strenghts data science & design team	**weakness** integrating data science in design innovation
opportunity supporting large enterprises on DDI	**threat** losing relevance to innovate with enterprises

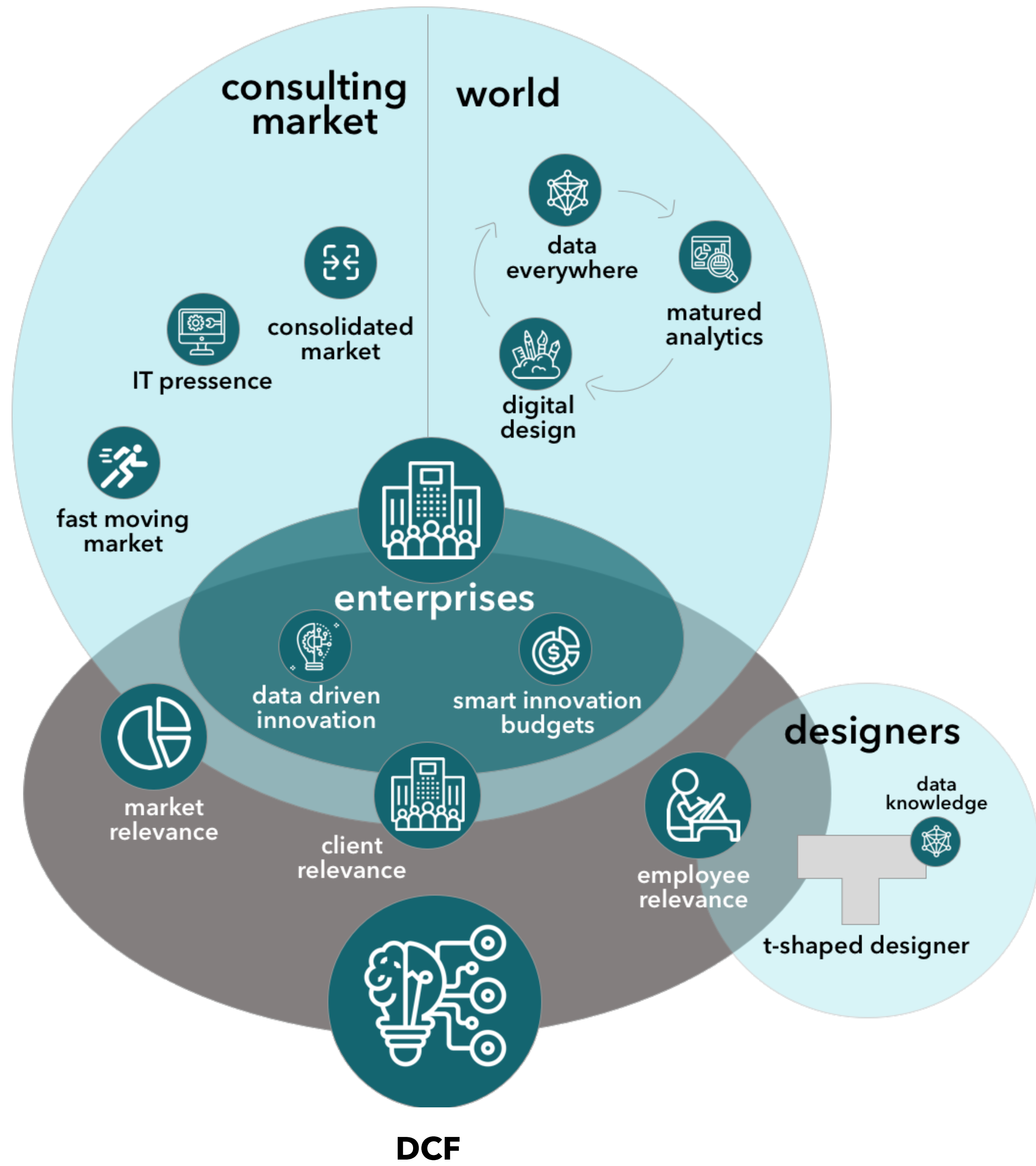
Figure 1.3 - SWOT analysis of DCF

by most organisations due to the presence of a large readiness gap (Deloitte 2020). The fact that data-driven design will be essential in innovation activities of large enterprises and that most of these organisations currently are not ready provides work opportunities for DCFs consulting these organisations. However, not being able to support enterprises could pose a threat. The consulting market is consolidating (Gartner, 2019) and perceives the entrance of large IT-native consultants (e.g. google providing consulting). Consequently, not supporting enterprises with DDI risk losing innovation projects to clients to more suitable consultants.

Essential for the survival of organisations is a firm's capability to learn and adapt to its changing context Kim and Lee (2006). To respond to this changing context, the DCF has a data science and design team. However, during initial interviews, employees indicate that collaboration between the DCF's data science and design team is an issue. Both teams lack knowledge on how to collaborate, and the overall firm lacks knowledge on how to integrate data science in innovation. This lack of knowledge is problematic for the DCF, as the entire consulting industry is based on 'knowledge asymmetry' between the consulting and clients (Howden & Pressey, 2008). Consultants are hired because they can offer a suitable combination of knowledge currently not present at the client (Løwendahl, Revang and Fosstenløkken, 2001).

To conclude, data design innovation provides both an opportunity for the DCF as a threat - losing relevance to innovate with enterprises. Although the DCF has a data science and a design team, the firm needs support integrating data science in design innovation. From this perspective, the two research questions are drafted. How can data science and design innovation integrate at digital consulting firms? Furthermore, how can the data-design integration be facilitated at digital consulting firms?

Figure 1.4 - Future scenario - conclusions from DCF trend analysis



1.1.4 Designers

This thesis is written as a graduation thesis from the faculty of Industrial design at the TU Delft. In recent years, design students have an increase of interest in exploring how they could apply data science as a creative design method (Kortuem, 2020). While not a new concept, "T-shaped" hybrid designers, who work across functions while retaining their depth of design savvy, will be the employees most able to have a tangible impact through their work (McKinsey, 2018)

From a personal point of view, exploring how we as designers can strengthen the field of design with data science feels a crucial activity to undertake. According to Harvard Business Review, the role of data scientists has become "the sexiest job of the 21st century". And this is noticeable in the popularity of data and computer science studies, job directions and even daily conversations. But when a designer is asked what data science actually is, most of the time data science feels like a magic black box that can answer all the questions along if you are creative enough to feed it the right questions. We as designers should become reasiliant for a future where AI could challenge our fundamentals as designers, ie. human centered thinking, iterative working and abductive reasoning (Verganit et al., 2020). Verganti and others (2020) argue that AI not only incorporates the three essential principles of design thinking but outperforms human- centered innovation by eliminating human- intensive limitations. They suggest that in big- tech driven firms, problem solving will be replaced by computers and designers will shift their focus to problem finding. Kun and others (2018) however, argue that designers can use their abductive reasoning during exploratory data analysis in order to generate hypotheses. While both imply a changing role for designers towards the start of the innovation, one was conducted with master level students and the other based on big-tech driven firms.

The question remains if both are applicable to other contexts. As in the context of this research: designers in consulting organisations with in- house data scientists providing digital innovation. From this perspective the following research question is drafted. What could the role of designers be in the future of data-design innovation at digital consulting firms?

1.2 Project Objective and approach

This subchapter elaborates the research objective. The research questions are drafted and detailed by identifying the project objective, the project scope and the perspective throughout these are answered. This subchapter provides a better understanding of which areas focus will be and through which eyes these questions are answered. This understanding is essential, as this determines the perspective through which the research findings are drafted.

1.2.1 Thesis Goal

Based on the initial empirical investigation, the following three research questions are drafted. The first two research questions are answered by research for design. This thesis aims to explore and design practical support for consulting organisations that enable integrating data science in their current design approach to innovation. This is done by exploring the main internal challenge and learning from valuable integrations to achieve integration between both teams. Alternatively, the latter research questions will be answered by design for research. This question aims not to design practical, but rather to inform the design discipline and design practitioners about future roles. The research and the designed solution will be reflected during the discussion.

RQ1 How can digital consulting firms integrate data science in design innovation?

RQ2 How can this data-design integration be facilitated in digital consulting firms?

RQ3 What could the future role of designers be?

Worldview - pragmatic constructivism

With the aim of this thesis to add knowledge to the firm's design and data team, the philosophical worldview pragmatic constructivism is used. Constructivism is an approach to learning that holds that people actively construct or make their knowledge and that reality is determined by the experiences of the learner (Elliott et al., 2000). Learning in the perspective of pragmatic constructivism is analysing and reducing the truth gap between 'proactive truth' and 'pragmatic truth' (Nørreklit, 2011). By participating in an activity, individuals become more proficient in doing it and construct a deeper understanding of the rules, methods, and goals of this activity (Dewey, 1988). In Dewey's view, genuine knowledge comes from integrating thinking and doing by getting the mind to reflect on the act (Gordon, 2009).

Stakeholders

The project takes place between the faculty of Industrial Design Engineering (TU Delft) and a DCF. The project involves three internal teams: Creative (Design), Strategy & Data Science.

Target group - design data decision-makers

According to the Cambridge dictionary, organisations are "a group of people who work together in an organised way for a shared purpose". From this perspective, the DCF is merely a construct describing a wide range of stakeholders. The target group of this thesis is the DCF's data science and design teams. This target group is later detailed as the data science and design teams' decision-makers based on empirical research. Although the target groups are the data and design teams, other stakeholders (management, clients) are included to provide a holistic understanding of the context.

Scope
DCF
This thesis is written in collaboration with a DCF. The proposed solution is designed with the DCF's data and design team as the primary target group.

Design point of view
In this thesis, the integration from both teams is mainly focussed from a design point of view. Meaning, what can data science mean for design? This thesis does not argue that that is the perspective to be taken, but mainly as the background from the author entails a design background.

Organisation perspective
In this thesis, data-driven innovation is explored from an organisational point of view. It is not explored (in-depth) on the product and process level. The aim is to explore the DCF as organisation, how its needs to adapt and the applicability of data science in DCF's design innovation client projects.

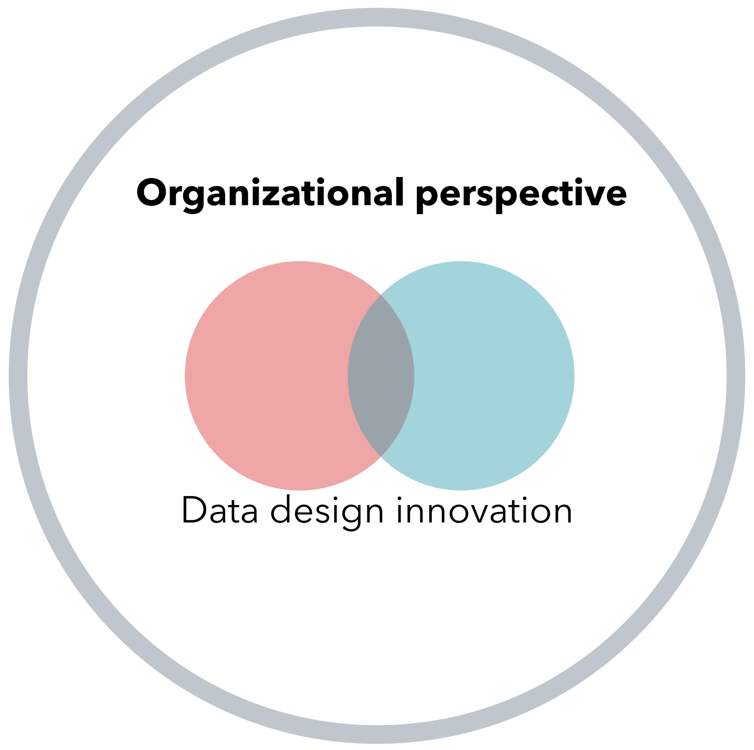


Figure 1.5 Research perspective - data-driven design innovation from organizational perspective

1.2.2 Methodology
The initial empirical investigation suggested an essential element of consulting firms, and the problem of the DCF in question is how it acts with knowledge or information. In addition, this thesis aims to explore and design practical support for the DCF. For this reason, the research approach is based on design science in information systems research (Hevner et al., 2004). The authors propose an approach of both design science and behavioural science to research information systems in business. The behavioural sciences paradigm aims to develop a theory of why certain phenomena occur related to the business needs (i.e. why are the employees not able to integrate) in order to develop the 'truth'. The design science paradigm aims to address important unresolved problems, often considered wicked problems (Webber, 1984), in new ways by building and evaluating artefacts to develop a utility for the firm (Hevner et al., 2004).

In addition, the seven guidelines (proposed by (Hevner et al., 2004., p83) are used to guide the research process, including business problem directed research (Guidelines 2), the use of design as a search process (Guidelines 6) and the design and evaluation of IT artefacts (Guideline 1). Authors

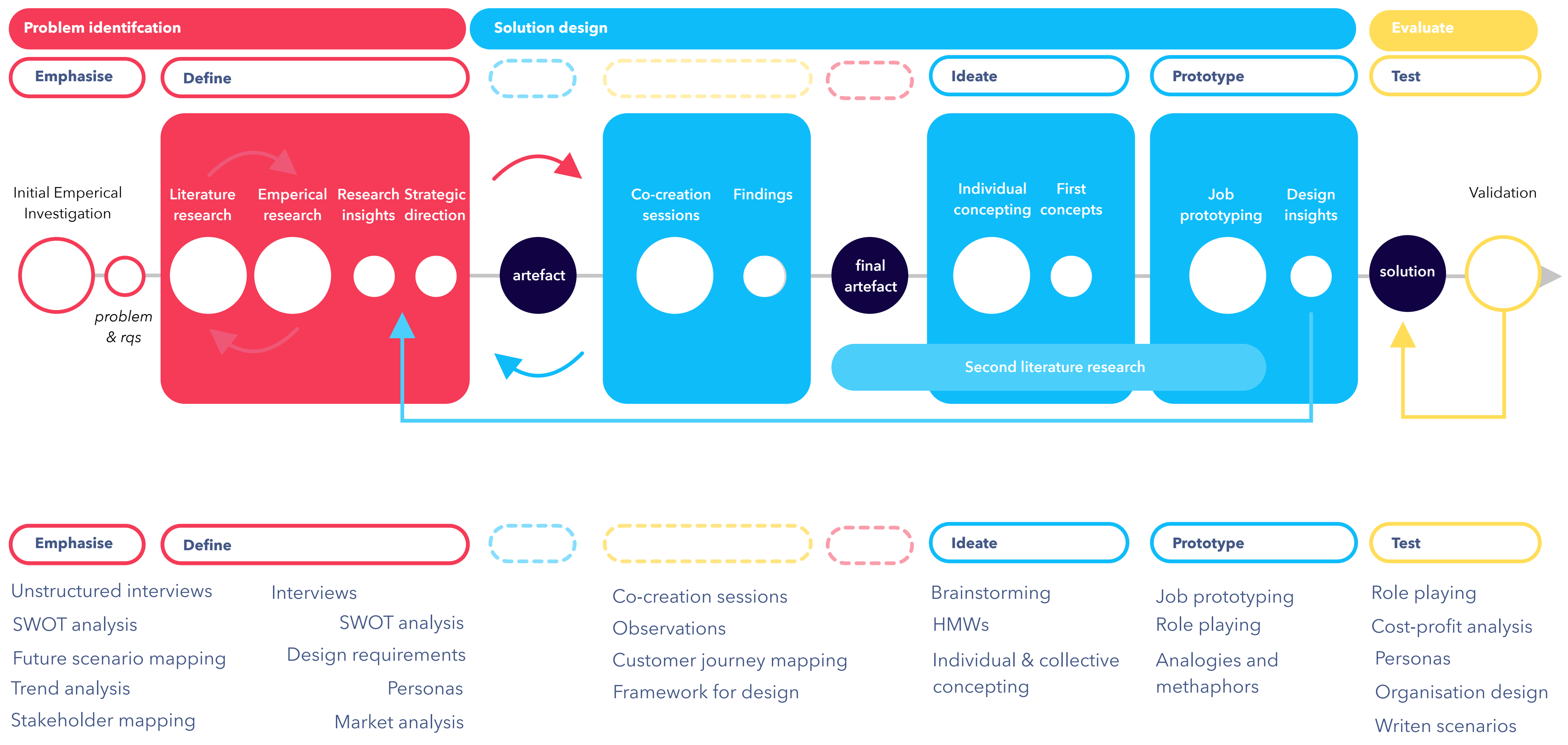


Figure 1.6 - Iterative design science research process, adapted from (Offermann et al., 2009), Hasso Plattner Institute of Design at Stanford, n.d.) and (Hevner et al., 2004., p83)

argue that the purpose of design science research in IS, by definition, is to create purposeful, viable IT artefacts to address a fundamental organisational problem. Authors argue that this artefact can be in the form of a construct, model, method or instantiation (Hevner et al., 2004., p82) but emphasise the IT as "core subject matter" (Hevner et al., 2004; Orlikowski and Iacono, 2001). This research challenges this view. Based on research findings, an emphasis is concluded on the person-to-person knowledge transfer. Chapter 5 elaborates in these findings and proposes a different way of generating and evaluating artefacts. For this reason, this thesis views artefacts as more broadly in the perception towards the organisation, policies and practises as designed artefacts (Boland, 2002). This view is in line with the view that artefacts can be innovations that define ideas, practises, technical capabilities and products for which information systems can effectively and efficiently be accomplished (Denning, 1997).

1.2.3 Process
This section elaborates on the research process. This process in figure 1.6, is based on two approaches; the design science research process; identification-solution design-evaluation (Offermann et al., 2009) and the d.school design thinking process (Plattner, Meinel and Weinberg 2009). The d.school five-step approach, emphasise-define-ideate-prototype-test, is used to apply more practical design methods (visualised bottum part figure 1.6) Although the process is sequential visualised, in practice, this process is more iterative of nature. For this reason three iterations are visualised in figure 1.6. This section briefly elaborates on the activities performed in the five phases.

Last, the Organisational Design Framework of Stanford (2007) is used to guide the research. Consulting firms are generally defined by complexity (Dunford, 2000). Stanford's framework's holistic nature is highly applicable to identify and address the complexity of researching DCFs by determining sublevels (see figure 1.7). It allows to research parts of the organisation individually and recognises inter dependability between findings in these levels. According to Stanford, organisation can be compared to a 'gyroscope', meaning all organisational elements are strongly interrelated and need to be addressed in the analysis to form a holistic perspective.

Problem identification
Emphasise: The goal is to understand the practical context of the DCF, identify and conceptualise potential business problems, and draft research opportunities (Hevner et al., 2004., p8). Employees are interviewed to construct these findings. These led to the formulation of initial research questions.

Define: This phase aims to understand the concepts of data design innovation and the integration and facilitation in the practical context of DCFs. First, literature research is performed to strengthen further the current theoretical understandings of data science, design innovation and integrations. The urge for empirical research is withdrawn from this literature research. To answer this research practise gap, empirical research is conducted with the DCF in question. In practice, the literature and empirical research are more iteratively performed to provide scope continuously. This leads to both research findings and a strategic design direction.

Solution design
Artefact: In line with the strategic design direction, an artefact is designed based on the synthesis of research findings. This artefact visualised the theory "in a socially recognisable form" (Orlikowski and Iacono 2001, p. 121) and is used during multiple co-creation sessions to evaluate the utility of the design in the practical context. Based on the evaluation findings, both the artefact itself has refined and the research findings and the strategic design direction (as visualised by the arrows). This led towards a final chosen design direction and a framework for design.

Ideate: To increase the utility and applicability of the designed artefact in the organisation, ideation is performed to generate many ideas and develop the first concepts. During this step, additional literature research is performed to increase the understanding. This led to the design and prioritisation of three concepts.

Prototype: In this phase, the concepts are iterated several times. The prototyping phase is based on a proposed job prototyping method in design science in information systems research (Hevner et al., 2004). Job prototyping can be viewed as an approach to rapidly prototype, test, and improve new jobs inside organisations before hiring a new job holder.

Evaluation
Test - Final validations are performed with the DCFs employees to validate the final design (including the artefact). Validation is essential to determine what works, what the actual value is to stakeholders, and understanding the impediments and providing final improvements to the design (Offermann et al., 2009). In addition to the data science and design teams, many stakeholders are included to validate the final design from a complete perspective. In order to simulate the practical context, role-playing is used. This phase led to a final set of recommendations in order to increase strategic fit with the organisation.

"Organisational design is like a gyroscope"
- Stanford (2007)

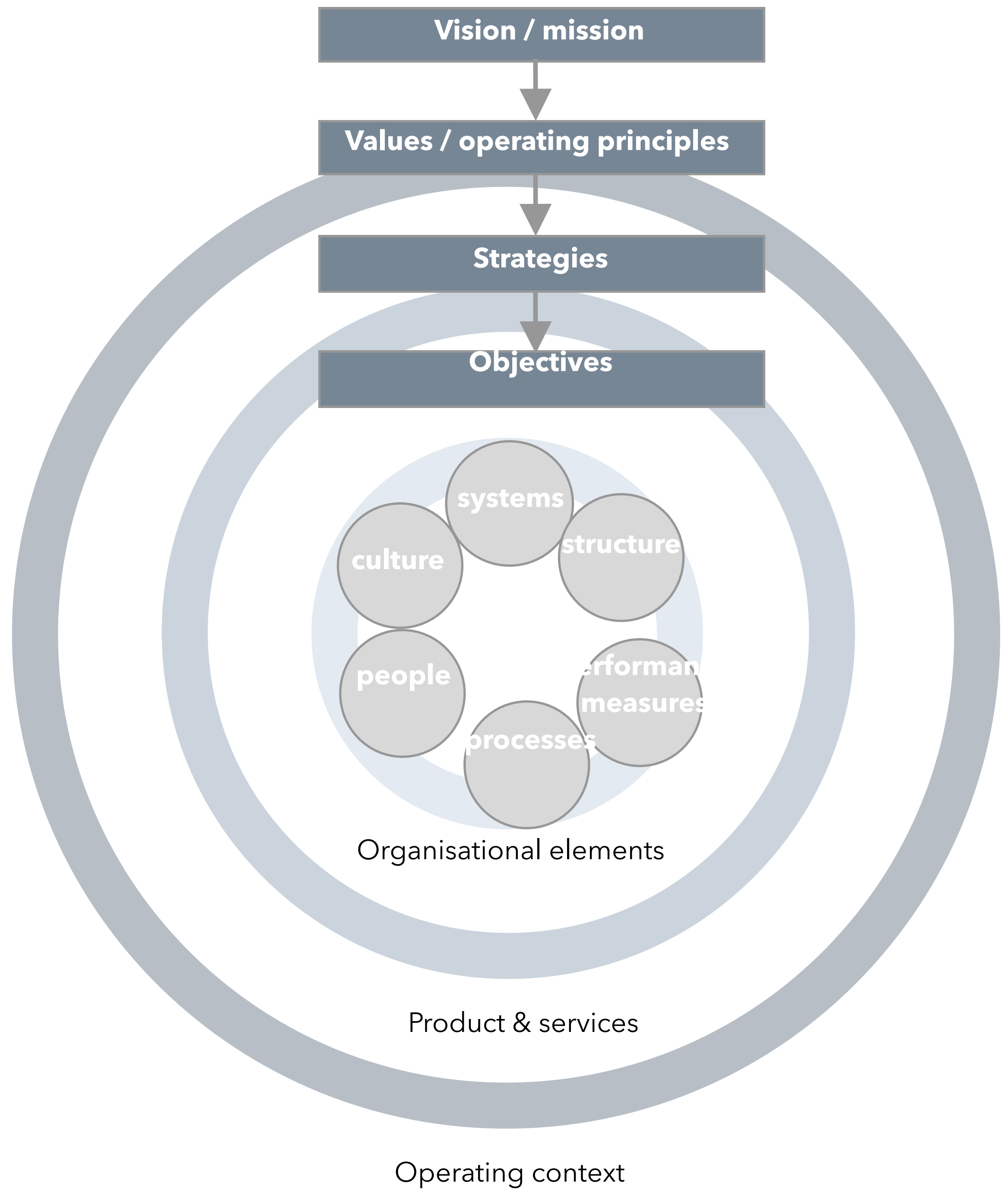
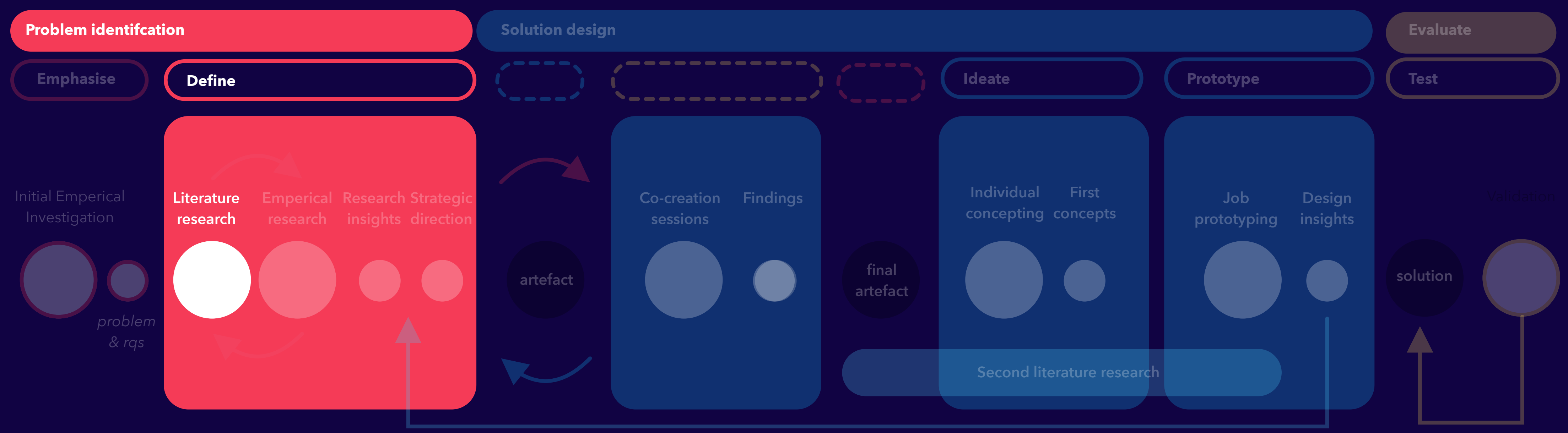


Figure 1.7 - visual representation of organisation design (Stanford, 2007)

2. Literature research

This chapter aims to bring an understanding of data design innovation and facilitation of consulting firms. The first subchapter explores data science and design innovation and discusses the current data-design literature. The second subchapter explores the 'learning organisation' in relation to consulting firms by the concepts of knowledge. learning and leadership. The chapter synthesises these two studies and formulates a practise research gap.

2.1 Data design integration
2.2 Facilitation at digital consulting firms
2.3 Research practise gap



2.1 Data design integration

This subchapter explores the fields of data science, design innovation and the integration of both in the context of organisations through a literature study. The concept of data, the reason of interest from organisations in data and different data types are explored. A framework is provided to highlight the difference in data from data science and a design perspective. The discipline of data science is explored by elaborating commonly used terminology and discussing the process behind data science. Design thinking and its use in innovation are explored. The integration of data science and design innovation is explored. The subchapter is concluded with the draft of the practice research gap regarding data design integration.

2.1.1 Data

The use of data for organisation's innovation efforts has become imperative for survival (Cronhol, Goble & Rittgen, 2017). However, what is *data*? *Data* can be seen as a 'raw material'. *Data* is "discrete, objective facts or observations, which are unorganised and unprocessed and do not convey any specific meaning" (Rowley, 2007, p. 165). This definition suggests that *data* itself has no specific value and has to be organised and processed.

Ackoff's Knowledge pyramid (1989) is commonly used to understand data processes, as it provides a better view of what information is useful for specific purposes (Rowley, 2007). In figure 1, the pyramid's four layers are visualised; data-information-knowledge-wisdom. To elaborate on these terms. Data can exist in any form and does not have meaning. Information consists of processed data directed at increasing its usefulness (Ackoff). The difference between data and information is functional, not structural. Questions that can be answered with information are who, what, when, where, and how many. Knowledge is the appropriate collection of information, such that it intends to be helpful but does not provide further knowledge. Knowledge allows answering how-to questions. Finally, wisdom is how people can take knowledge and synthesise new knowledge from the previously held knowledge. Wisdom provides answers to 'why' questions. This process of moving 'higher up the pyramid' is especially interesting for organisations because it allows them to base decisions on that extracted knowledge. From this perspective, data and information become knowledge assets that can create value for firms (Cricelli & Grimaldi, 2008).

Thick versus thin data

The "split in the data universe" of Bornakke and Due (2018) is used to understand better what data is. The authors divide the data landscape into two common categories; big-thin and (small) thick data. This 'split' is especially applicable to the context of this research - data science and design.

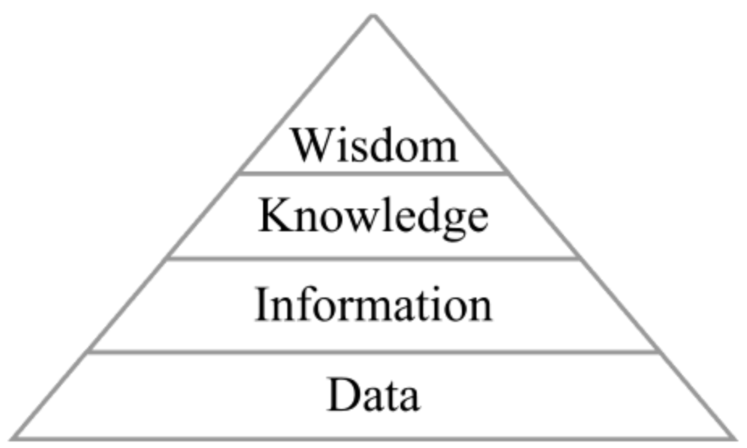


Figure 2.1 - Ackoff's Knowledge pyramid (1989)

In Figure 2 different typologies of data are placed on a double-axial framework - thin versus thick description and extensive versus small data. The thickness of the description determines how much context is provided with the data (Bornakke and Due, 2018). To provide an example, age itself is just a number (and thus thin), but age-linked towards a person's name or even behaviour is more extensive in context. The more one knows of a specific data, the more descriptive and thicker it is. Big-thin data, otherwise commonly referred to as 'Big data', is characterised as extensive in amount but thin (Bornakke and Due, 2018). For example surveys, large data sets. Small thick data refers to the opposite: thick descriptive but small in numbers, commonly used in the design, and generated by qualitative or ethnographic methods like interviewing and observations. These two typologies can be compared to the two fields of data science and design. Whereas data science uses big data sets to inform decision making, the design discpiline focuses on ethnographic methods like interviewing and observation.

To conclude, data in itself does not convey any specific meaning and has to be processed to provide helpful information, knowledge or wisdom. The process is precious for organisations for data-driven decision making. Data can be types as big thin data - used for data science, and small thick or qualitative data - used in the design. The following sections will explore these two disciplines in depth.

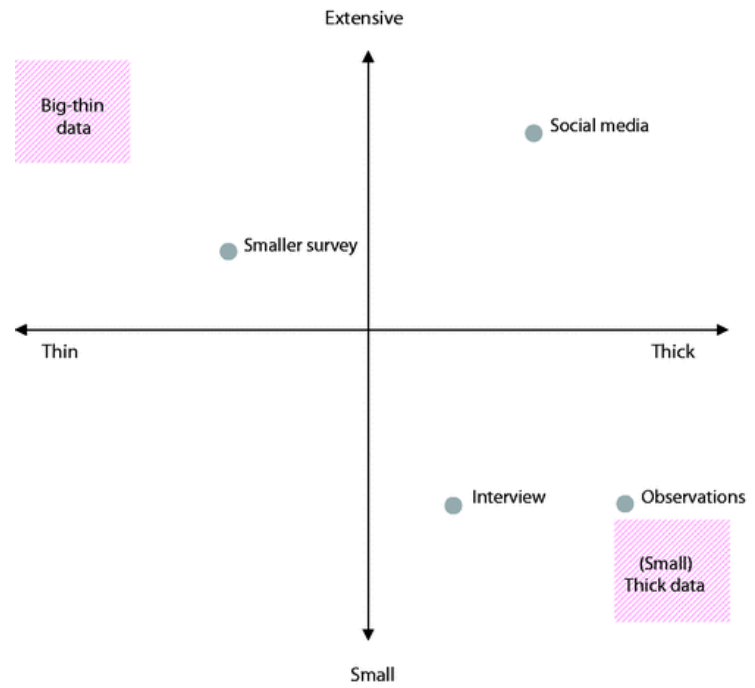


Figure 2.2 - The "split in the data universe" from Bornakke and Due (2018)

2.1.2 Big data and data science

Data science is a set of fundamental principles, processes, and techniques that guide the extraction of knowledge from data via data analysis (Provost & Fawcett, 2013). This section aims to understand data science by elaborating four commonly used terms and discussing the relationship between these (see figure 2.3).

First, big data is defined as "describes large volumes of high velocity, complex and variable data that require advanced techniques and technologies to enable the capture, storage, distribution, management, and analysis of the information." (TechAmerica Foundation's Federal Big Data Commission, 2012).

"Big data is worthless in a vacuum. Its potential value is unlocked only when leveraged to drive decision making." (Gandomi and Haider, 2015).

Big data refers to datasets that are too large for traditional data-processing systems and require new technologies (Provost & Fawcett, 2013). To enable DDD, organisations need 'big data processes' to transform the high, fast-moving and diverse data into meaningful insights (Gandomi and Haider, 2015). Gandomi and Haider propose a process consisting of steps in two stages: data management and analytics. Data management involves processes and supporting technologies to acquire and store data and prepare and retrieve it for analysis (Gandomi and Haider, 2015). If data can be compared to a 'raw material', engineering and processing can be compared to pipelines, critical to supply the data to perform data-science activities.

Data science can be seen as a part of the field of data analytics. Data analytics is defined as "the ability to acquire, store, process and analyze large amounts of data in various forms, and deliver meaningful information to users that allows them to discover business values and insights in a timely fashion" (Kung and Byrd 2018.p 3). Figure 2.4 positions data science concerning data analytics and the context of business.

Comparable to Ackoff's Knowledge pyramid, Business intelligence aims to answer what questions, for example, reporting with visuals of past business performance. Business analytics aims to answer questions to the why, for example, sales forecasting) (Chiang and Storey, 2012). Last, to clarify, Artificial intelligence (AI) refers to "the ability of a digital computer or computer-controlled robot to perform tasks commonly associated with intelligent beings" (Coopeland, 2020). AI can also be applied to BI&A, for example, creating real-time dashboards that continuously show past business performance results

An important characteristic of data science is the data science hierarchy of needs. The hierarchy of needs (visualized in figure 2.5) can be compared to Ackoff's Knowledge pyramid. The higher the hierarchy, the more context certain information contains and the more value it can create for a firm but the more effort it takes to provide a valuable results (and more data resources).

To conclude, data science can be viewed as a set of principles, processes, and techniques to extract knowledge from data by analysing that data (Provost & Fawcett, 2013). For businesses, the importance of using data science is to base decisions on that extracted knowledge. Otherwise referred to as data-driven decision-making (DDD), i.e. "the practice of basing decisions on the analysis of data, rather than purely on intuition." (Provost and Fawcett, 2013). However, before any decision can be provided by data analytics, data has to be managed. Last, the more context a piece of specific information is required to provide, the more is needed to provide an answer.

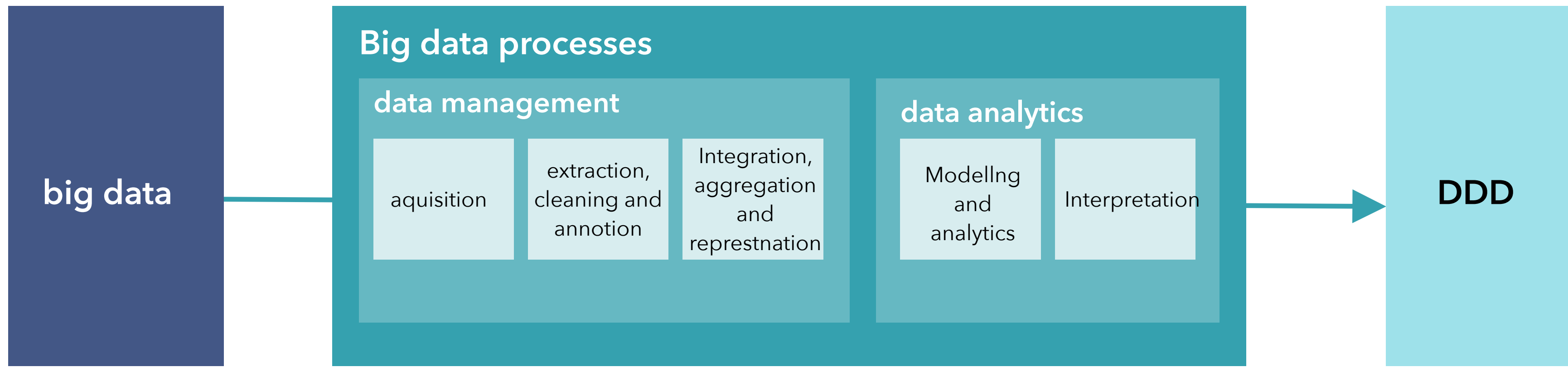


Figure 2.3 - Big data processes and terminology (Gandomi and Haider, 2015)

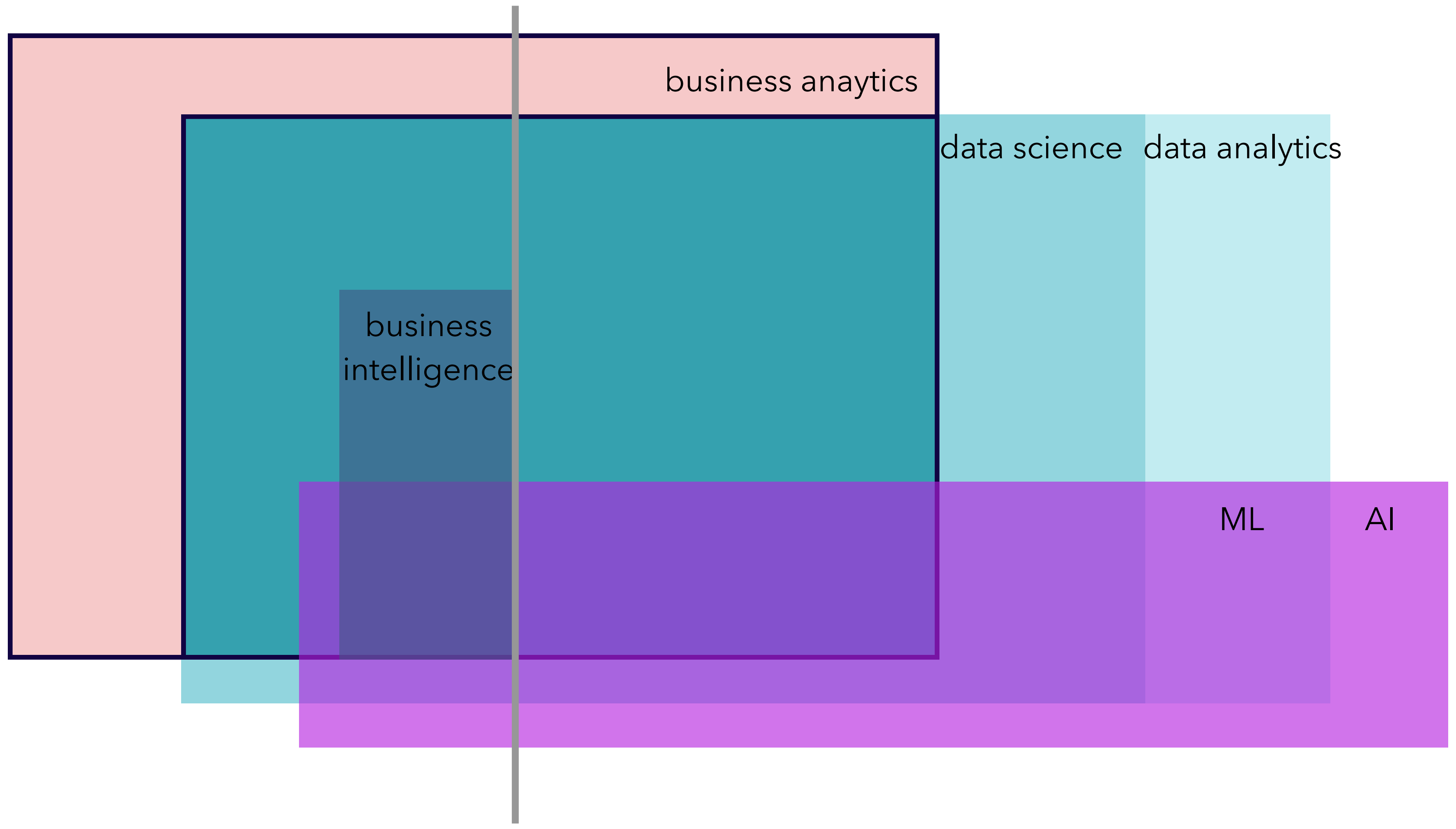


Figure 2.4 - The field of data science and its relation to data analytics and business, adapted from Data Science 365

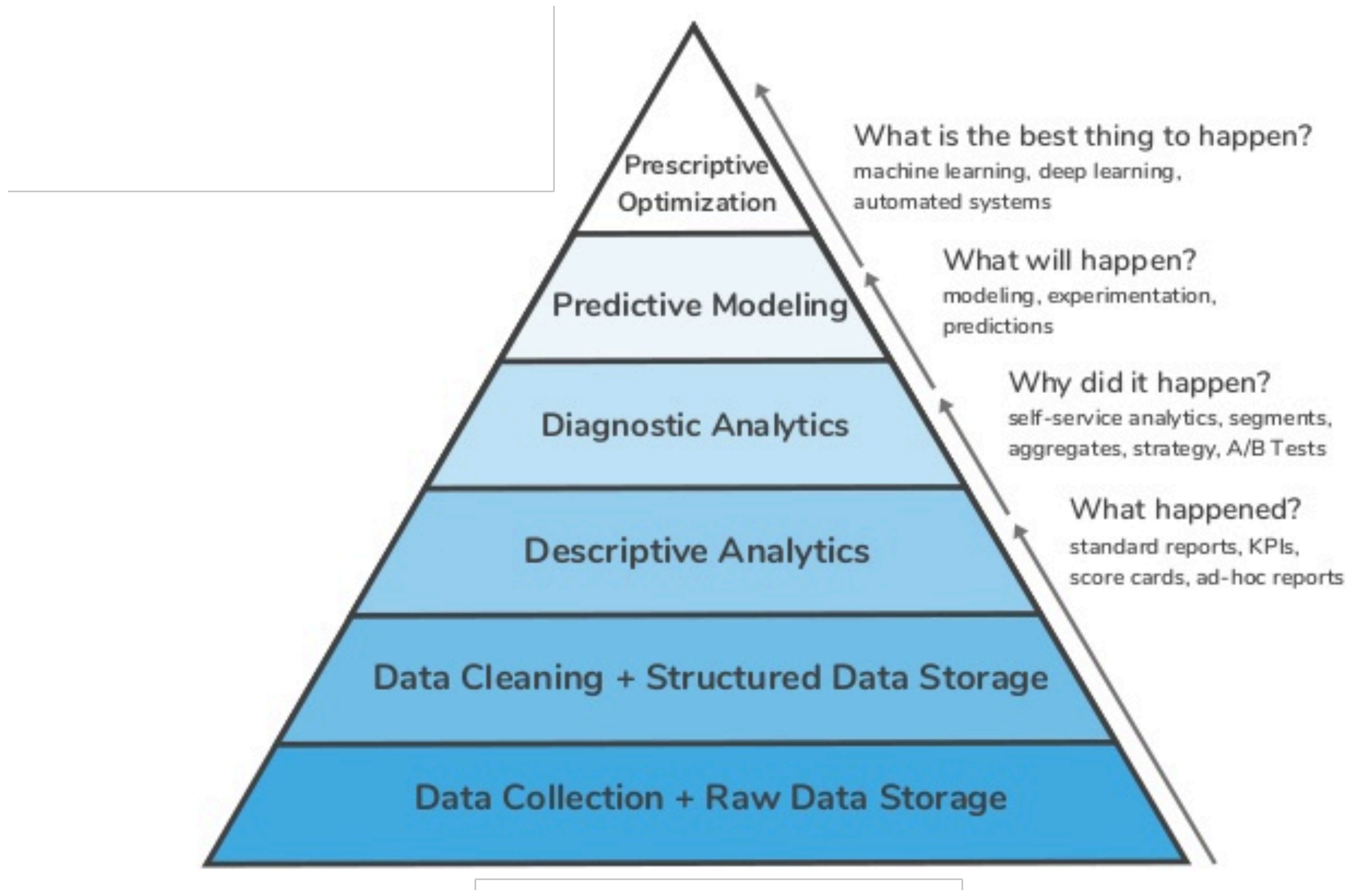


Figure 2.5 - Hierarchy of data needs in relation to decision making

2.1.3 Design innovation

In recent years, the discipline of design has been subjected to an 'upward move' into organisations, visible in the move from designing products towards services and interactions and currently towards the application in systems and organisations (Price, de Lille and Bergem, 2019). The concept of design thinking is ambiguous. Liedtka's definition in 2018 provides an elaborated definition of design thinking, "a systematic approach to problem solving, especially well-suited to a class of problems where the nature of the problem is people-centered, rather than technology or process centered, and uncertainty is high. It is hypothesis-driven, incorporating both generative and analytical thinking modes, and characterized by an emphasis on discovery of deep needs, collaborative work, optionality, iteration, and experimentation in practice"

Design innovation DCF

Design consulting has a strategic role in the client's innovation efforts by influence the client's strategic decision making (Calabretta et al., 2012). Calabretta et al. argue that design consultants can influence client's innovation efforts by a facilitating role, the design of artefacts (understand the market, become aware of core strengths, reduce the uncertainty of developing new offerings), or act as knowledge brokers (Canato & Giangreco, 2011). These activities suggest that design consulting has a broad influence on the client's innovation efforts. These innovation efforts can be categorised into four levels; strategy, resources, processes and mindset (Borjesson and Elmquist, 2012).

In the context of consulting, design can thus be viewed as the design of artefacts as interfaces, interactions, experiences, services and systems (Stappers, 2016), as a process to innovation and as a business strategy (Peppou et al., 2015). Due to the broad and diverse nature of design in DCF, this thesis takes the perspective of design as a practice to innovation, in line with Carlgren, Rauth and Elmquist (2016). These practices distinguish design innovation projects from other projects undertaken in organisations (Price, Klitsie and de Lille, 2019). Carlgren, Rauth and Elmquist argue that design is often related to five themes, user focus-problem framing-visualisations-experimentation-diversity, complementing principles and practices. Tabel 2.1 provides an overview of these practises and the client's innovation efforts. **In this thesis, design innovation is viewed as 'the performance of design consulting practises by digital consulting firms with the intend to influence the client's innovation efforts.**

Design theme	Design practise
User focus	Use qualitative context specific to user research
Problem framing	Challenge and reframe the initial problem
Visualisation	Make rough representations
Experimentation	Prototype quickly and often to learn
Diversity	Collaborate with external entities

Innovation effort	
Brojesson and Elmquist (2012)	**Lawson and Samson (2001)**
Strategy	Use qualitative context specific to user research
Resources	Harnessing the competetence base, management of technology
Processes	Organisational structure and intelligence, reward system, idea management
Mindset	Culture and climate

Table 2.1 - Design themes and example of practise from Carlgren, Rauth and Elmquist (2016) and innovation capacity (Brojesson and Elmquist, 2012; Lawson and Samson, 2001)

2.1.4 Data design integration

This section aims to bring an understanding of how data science and design innovation can be integrated. The integration has been coined by scholars in many different ways. Terms as data-enabled design (van Kollenburg & Bogers, 2019), data-driven design or 'Design inquiry through data' (Kun). Especially the term 'data-driven design' is found to be ambiguous. Table 2.7 provides an overview of the current scholar work on the intersection of both. Scoped in the introduction, a common application for the integration, design for data visualisation (Kirk, 2016; Bigelow, 2014; Osman & Mines, 2015) is not the focus.

To restate the definition of data-driven decision-making (DDD), i.e. "the practice of basing decisions on the analysis of data, rather than purely on intuition." (Provost and Fawcett, 2013). Ngai (2016) argues that intuition is still essentially valuable, but qualitative insights should complement quantifiable data. Data and analytics enlarge product understanding and ensure that decisions satisfy stakeholders (Ngai, 2016). This process design can use data and metrics to test and evaluate assumptions and hypotheses. Pardi (2017) supports this argument but places limitations on this intuition to be limited by memories, biases, and perspectives. Pardi argues that data should be used during the creative process, asking questions to discover insights and experimenting with potential directions.

	Data-driven design		Data-informed design		Data-enabled design
	Automated data-driven design	*Data-driven design*	*Data-informed design*	*Data aware design*	*Data enabled design*
Van Kollenburg et al., 2018	Data-driven design				Data-enabled design
King and Churchill, 2017[1]		Data driven design	Data informed design	Data aware design	
Speed and Oberlander, 2016	Design by data	Design with data			
Kun, Mulder and Kortuem, 2018		Design inquiry through data			
	When systems are designed by other systems, largely autonomous where new product and services can be synthesised via data intensive analysis	Data collected determines design decisions - answers well targeted questions, where data alone can help drive decision making	Data is only one input into decision making- allows to understand how your data-driven decision fit into large design space	Decisions made not just by data - recognizing that there are many related questions and also many related kind of data to answer and influence questions	Data-enabled design sets out to use data as creative material from the early stages of the design process to ascertain new design directions.

Figure 2.7 - Overview of literature regarding data design integration

These scholars highlight a dynamic between the position and influence of data-driven decision making (big thin data) and a designers' intuition' (small thin data) / ethnographic. - the position of ethnographic versus big data sets. Based on the synthesis of the different sources, this thesis proposes to use the following three terms

1. ***Data-driven design*** - data and the information generated by analysis/analytics directly determine the design innovation decision.
2. ***Data-informed design*** - data is used as one source to drive design decisions, alongside other data sources like user research or market analysis.
3. ***Data-enabled design*** - data is initially generated by first designing sensors, data is used together with thick data to iteratively imrpove the design.

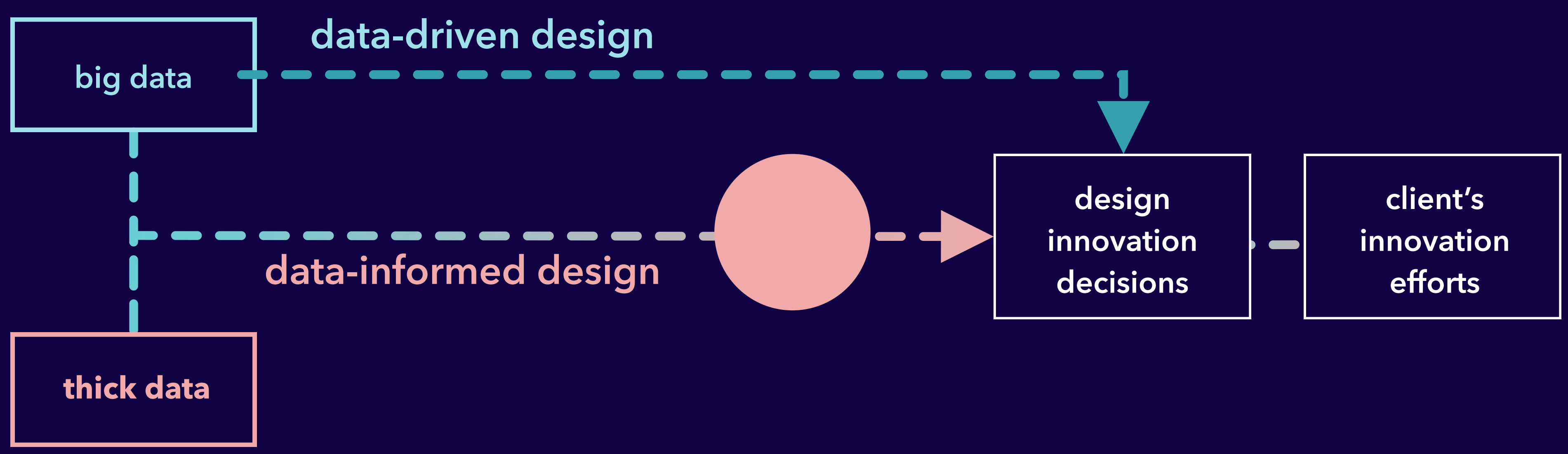


Figure 2.8 - Difference between data-driven design and data-informed design

Conclusions subchapter 2.1

Data in itself does not convey any specific meaning and has to be processed (Rowley, 2007, p. 165) Information can be extracted by these processes of levels of information, knowledge or wisdom (Ackoff, 1989). Each level provides more context in the research in order to provide information for decision making. Data can be split in two common types; big data - used as source in data science, and small thick or qualitative data - used in the design discipline (Bornakke and Due, 2018).

Data science can be viewed as a set of principles, processes, and techniques to extract knowledge from data by analysing that data (Provost & Fawcett, 2013). For businesses, the importance of using data science is to base decisions on that extracted knowledge. Otherwise referred to as data-driven decision-making (DDD). To compare this process with Ackoff's pyramid, the more context a piece of specific information is required to provide, the more data resources are needed to provide that answer.In addition, design consulting has a strategic role in the client's innovation efforts by influencing the client's strategic decision making (Calabretta et al., 2012). In this thesis, design innovation is viewed as the performance of design consulting practises by digital consulting firms with the intent to influence the client's innovation efforts.

The data-design integration can happen at three levels (see figure 2.8); data-driven design, data-informed design and last data-enabled design.

2.2 Facilitation

This subchapter aims to understand how DCFs can facilitate data-design integration by exploring the concepts of knowledge, knowledge management and learning. First, knowledge is understood and how it can be used as a strategic resource by organisations. The dynamic between knowledge, knowledge management, learning and the performance of organisations is discussed.

2.2.1 Knowledge transfer

Knowledge can be defined as "information which professionals acquire through experience and training, together with the judgement which they develop over time which enables them to deploy that information effectively to deliver client service." (Morris and Empson, 1998, p. 610-62). Knowledge can be individual or at a collective level (Kogut and Zander, 1992) and can be at a tacit and explicit level. Figure 2.9 provides a better view of what kinds of knowledge can be categorised in these levels.

According to Nonaka and Takeuchi (1995), knowledge can be transferred in four ways, depending on its level and how it can be transferred (figure 2.10). Socialisation refers to a tacit to tacit knowledge transfer, e.g. by observing others practises. Externalisation refers to a knowledge transfer by making tacit knowledge explicit, e.g. talking to a person about a specific experience. Combination refers to an explicit to explicit knowledge transfer and combining different sources of explicit knowledge to form new explicit knowledge. Internalisation refers to the transfer from explicit to tacit knowledge, e.g. reading documents to increase expertise (Nonaka and Takeuchi, 1995).

	explicit	tacit	
	Fact based knowledge- know-what	Experience based knowledge - know-how	dispositional knowledge - identify
Individual	facts, expertise	personalized knowledge (Hansen et al., 1999)	Aptitudes, intelligence, etc.
collective	codified knowledge (Hansen et al., 1999)	Norms, routines, best practises, shared 'ways of doing'	Shared culture, mechanism of socialization

Figure 2.9 - Knowledge types and levels, from Løwendahl, Revang and Fosstenløkken (2001) Knowledge and Value Creation in Professional Service Firms: A Framework for Analysis. Human Relations (p 918)

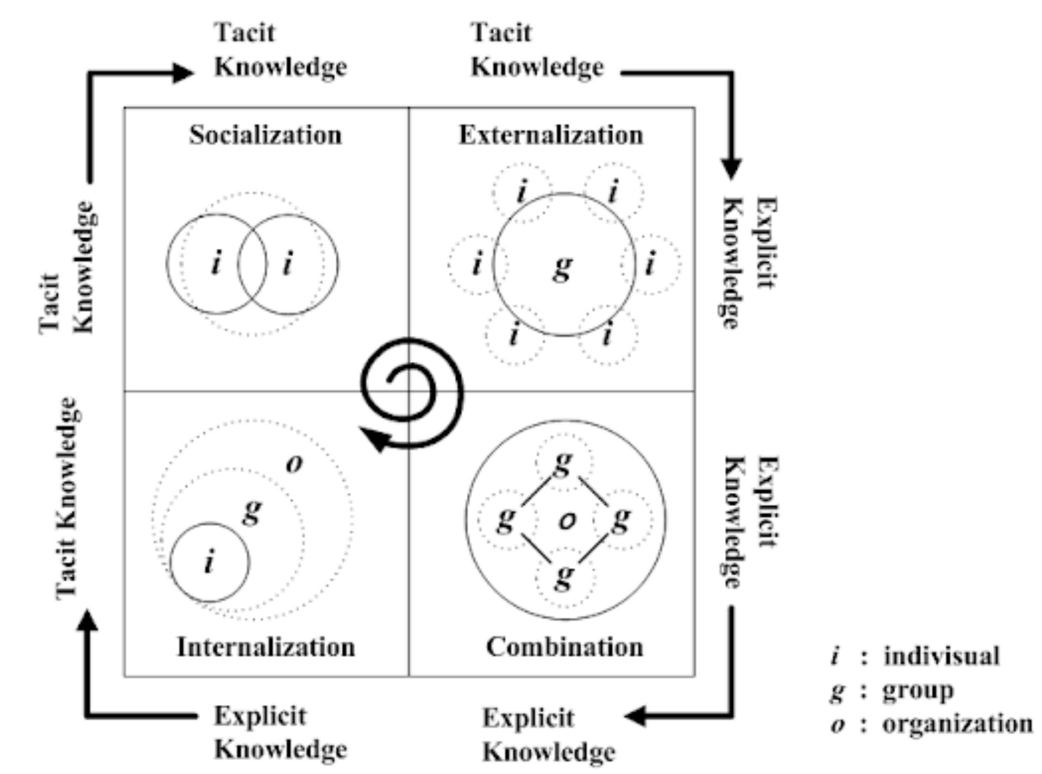


Figure 2.10 - Knowledge creation as the self-transcending process (SECI) from Nonake and Konno (1998), p43

2.2.2 Organisational learning

In the context of DCFs, knowledge is commonly viewed as a crucial resource to reach competitive advantage (Løwendahl, Revenge and Fosstenløkken, 2001). Resources are an organisation's asset base, tangible or intangible (Teece, 2009) and can be on a human, organisational, physical, technological or financial basis (Zubac et al., 2010). Løwendahl, Revenge and Fosstenløkken argue there are in general two ways knowledge can be used to reach competitive advantage; either (1) the resources themselves that are a source for sustainable competitive advantage or (2) resources are knowledge used as a source of innovation and value creation (Teece, 1998). The latter suggests a knowledge-based sustainable competitive advantage (Prahalad & Hamel, 1990), implying knowledge as a source for innovation.

Knowledge for innovation
In order to establish a knowledge-based sustainable competitive advantage, organisations must use their capabilities (Zubac et al., 2010). Capabilities are organisational processes in the most general sense, and their role is to change the firm's resource base (Bowman and Ambrosini, 2003). In figure 2.10.1, the organisation' internal dynamics of these organisational processes towards a knowledge-based sustainable competitive advantage are visualised. Knowledge management and organisational learning are two critical processes in organisations. "Through knowledge management, organisations seek to acquire or create potentially valuable knowledge and to make it available to those who can use it at a time and place that is appropriate for them to achieve maximum practical usage in order to influence organisational performance positively. (King, 2009). "Organisational learning refers to the activity of embedding what has been learned into the organisation (King, 2009). In turn, the exchange of knowledge and a collective management system that enhances organisational learning leads to innovation (Kim and Lee, 2006). Without these processes, the innovative capacity of consulting will decrease over time (Taminiau, Smit and de Lange, 2009). To reframe, knowledge can be used by organisations as a strategic resource. Having a collective system of knowledge management and organisational learning leads to innovation. To refer back to the aim of this thesis, innovation leads to the development of relevant, innovative service offerings, as in the case of integrating data science in design innovation.

Digital consulting firms
In the specific case of consulting firms, knowledge can be developed in two ways; on-the-job or internal effort. First, on-the-job refers to the knowledge acquired by individual consulting from performing projects with clients and the projects (Løwendahl, Revenge and Fosstenløkken, 2001). Second, internal effort refers to the sharing of knowledge, for example meetings or training.

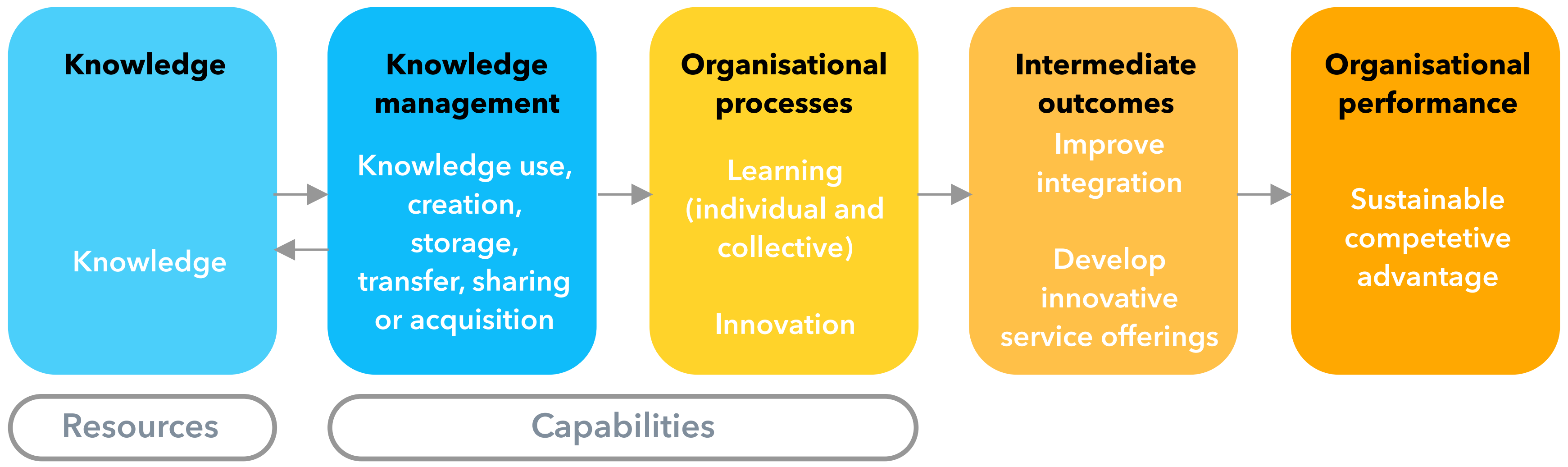


Figure 2.10.1 - Framework for organisational learning - process for knowledge-based sustainable competitive advantage, adapted from King (2009) and Zubac et al., (2010)

Knowledge transfer strategies
In the context of DCFs, the four knowledge transfer types can be divided into two 'knowledge strategies' - codifications versus personalisation (Hansen et al., 1999). Codification refers to the process of sharing, storing and transferring knowledge (by for instance IT systems or knowledge banks). This knowledge strategy is only applicable if the knowledge can be made explicit (e.g. tacit-explicit-tacit). This type of knowledge transfer is mostly used in 'reuse economics' consultants (Hansen et al., 1999). This refers to a low degree of customizations, when organisations have fine tuned solutions to standardized problems Dunford (2000).

The second knowledge strategy 'personalisation' is a knowledge strategy that emphasizes development of individual and personal knowledge and is suited for knowledge that cannot be made explicit. This type of knowledge transfer is mostly used in 'expert economics' consultants - with a high degree of customization Consulting firms that highly customize solutions to unique problems Dunford (2000). Dunford argues that in these contexts firms need to use interpersonal networks to facilitate information sharing. Interpersonal networks refer to the connection employees have in the form of direction relationships (Idris and Saridakis, 2018) , either social or business (Björkman and Kock, 1995) and can be defined as a group of people obtaining advice, information or support from a knowledge owner perspective (Dubini and Aldrich, 1991).

Although these two strategies take into account the firm and the type of knowledge that is aimed to be transferred, it does not account for any differences between the actors of knowledge transfer. This thesis researches the intersection between data science and design - and thus data scientists and designers. The 'commensurability' (ie. ease of giving information the same meaning) is influential for the effectiveness of a knowledge transfer (Arduin, Grundtstein & Rosenthal Sabroux, 2013). Especially the codified knowledge seems to only enlarge possibility of interpreting the information differently. (Arduin, Grundtstein & Rosenthal Sabroux, 2013). From these two perspectives, the DCFs firms economic model and the possible difference between the actors of knowledge transfer, figure 2.11 proposed a framework.

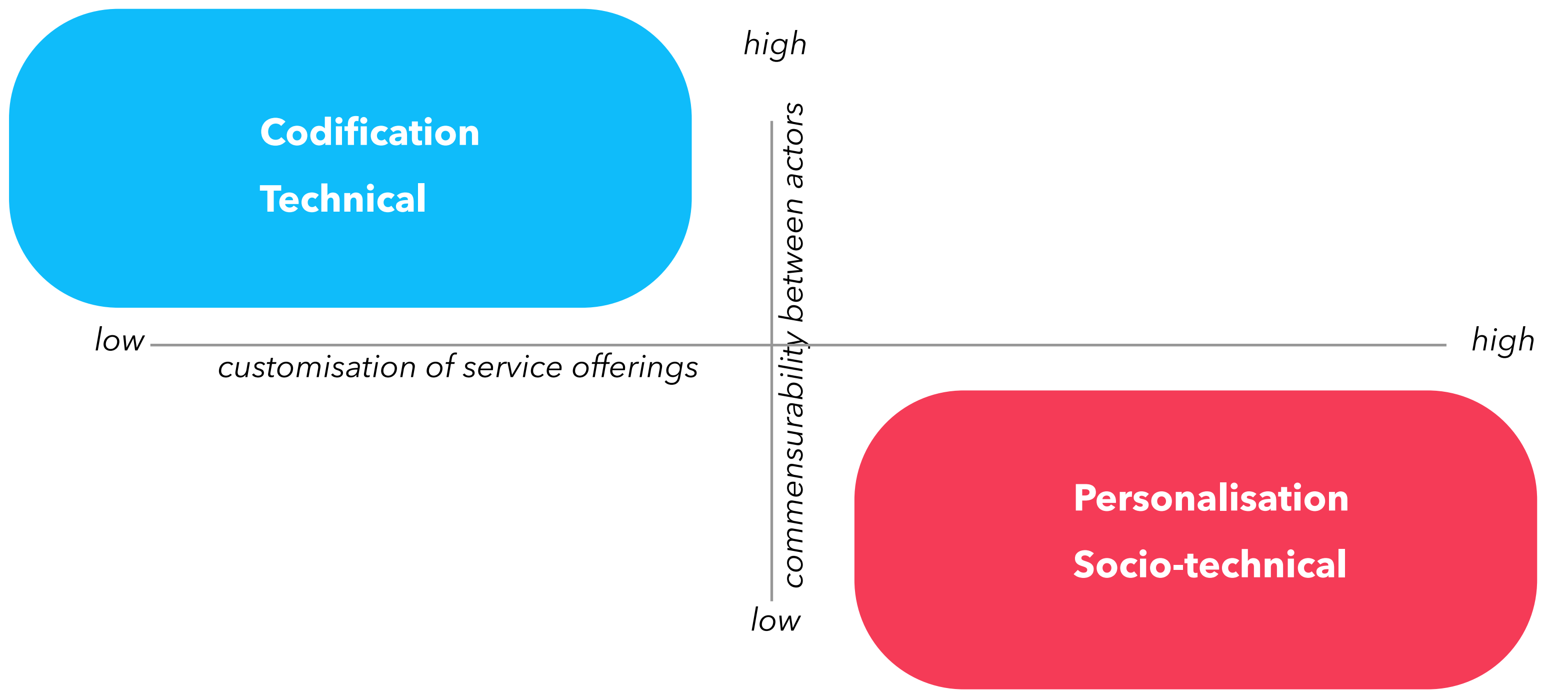


Figure 2.11 Two knowledge strategiescustomisation versus 'commensurability' - adapted from (Arduin, Grundtstein & Rosenthal Sabroux, 2013) and (Arduin, Grundtstein & Rosenthal Sabroux, 2013).

2.2.2 Organisational

Knowledge leadership - formal or informal

Nonaka and Takeuchi (1995) argue that managers should function as knowledge leaders by providing a knowledge vision, activity support, knowledge management, provide places for learning (called "Ba") and support knowledge transfer. In line with the concept of "Ba", Arduin, Grundtstein & Rosenthal Sabroux (2013) argue the importance of meetings, as these increase knowledge retention, catalyze innovation, allow knowledge creation and increase collaborative decision making. However, in consulting firms, a lack of support of management on learning (e.g. Weiss, 1999; Dunford, 2000; Taminiau, Smit and de Lange, 2009) is found as managers who are mainly interested in revenues.
In addition, Taminiau, Smit and de Lange (2009) argue that managers should better support innovation by informal knowledge sharing. Formal knowledge sharing refers to all activities that are institutionalized by management to share knowledge or learn. Informal refers to all activities that facilitate knowledge transfer but are not designers for that purpose (Taminiau, Smit and de Lange, 2009).

Outcome - integration

In light of the thesis's aim to integrate data science in design innovation, the concept of integration is further elaborated from an organisational perspective. Integration can be viewed as 'the quality of the state of collaboration amongst departments required to achieve unity of effort by the demands of the environment (Lawrence and Lorsch, 1967, p. 11). This definition emphasises the state of collaboration between the departments. Commonly used categorisations of these states are multidisciplinary, interdisciplinary and trans-disciplinary. In figure 2.12, a framework proposed by Nicholson and Armitage is used to show five internal activities. The framework allows both to categorise the state of integration of the data and design teams in the context and to provide direction which activities should be aimed for to increase integration. In addition, for collaborations aiming to move towards an interdisciplinary approach, five activities are essential, (1) creating interdependence of the disciplines, (2) support the collaborative creation of new professional services, (3) flexibility between the two teams, (4) foster a sense of collective ownership, and last (5) bring about a reflection of the process between the two teams (Bronstein, 2002).

	Multi	Inter	Trans
Assessment of client needs	separate by team members	separate with consultation	comprehensive assessment together
Service plan development	team members develop separate plans for	Team members share seperate plan with each other	Team members develop offerings and opportunities together
Staff development	independent within each discipline	independent within as well as outside of own	an integral component of team meetings for
Communication	informal lines	periodic case specific team meeting	regular team meetings with ongoing transfer of
Guiding philosophy	team member recognize the importance of contribution from other disciplines	team members willing and able to develop, share an be responsible for providing services that are part of the total service plan	team members make a commitment to teach,

Figure 2.12 - Multi, inter, transdisciplinary collaborative practices adapted from Nicholson and Armitage (2000)

Conclusion - research practise gap

Subchapter 2.1 aimed to increase understanding of data science in design innovation. The research on organisations' interest in big data and data science for innovation is extensive. Many authors argue the data science practice to extract knowledge from large data sets for data-driven decision-making (Provost and Fawcett, 2013; Cronhol, Goble & Rittgen, 2017; Cricelli & Grimaldi, 2008).

Authors have explored the dynamic between data-driven decision-making and design, mainly emphasising the dynamic on the data level (King and Churchill, 2017; Speed and Oberlander, 2016); coning the terms data-driven, data-informed design and data-enabled design. In addition, the impact of design consulting on a firm's innovation effort is by strategic decision making is established in the literature (Calabretta et al., 2012). However, no work is performed on the relationship between consulting's design practices and data science for the client's innovation efforts.

Subchapter 2.2 aims to provide a better understanding of the consulting and could facilitate data-design integration. The term "learning organisation" has been around for a while (Senge, 1990), and much research has strengthened this understanding since. One worthwhile addition is the framework for knowledge systems (King et al., 2009) as mains to reach a knowledge-based sustainable competitive advantage (Prahalad & Hamel, 1990). Knowledge systems enhance organisational learning, leading to innovation (Kim and Lee, 2006) and increasing the innovative capacity of consulting organisations (Taminiau, Smit and de Lange, 2009). A conceptual framework is proposed to offer insight into two knowledge transfer strategies of a consulting organisation; codification and personalisation (Hansen et al., 1999; Dunford, 2000; Arduin). In addition, Taminiau, Smit and de Lange (2009) argue that managers should better support innovation by informal knowledge sharing.

However, these researches do not take any difference between actors into account. This is problematic because the commensurability between actors highly determines the type of knowledge strategy applicable (Grundstein & Rosenthal Sabroux 2013). Questions remain if these knowledge strategies are applicable in interdisciplinary integration, as in the data-design integration. Issues regarding the integration of data science in design innovation and the facilitation of DCFs remain unanswered. From both a research and a practical point of view, the need for empirical research is withdrawn.

How can digital consulting firms integrate data science in design innovation?

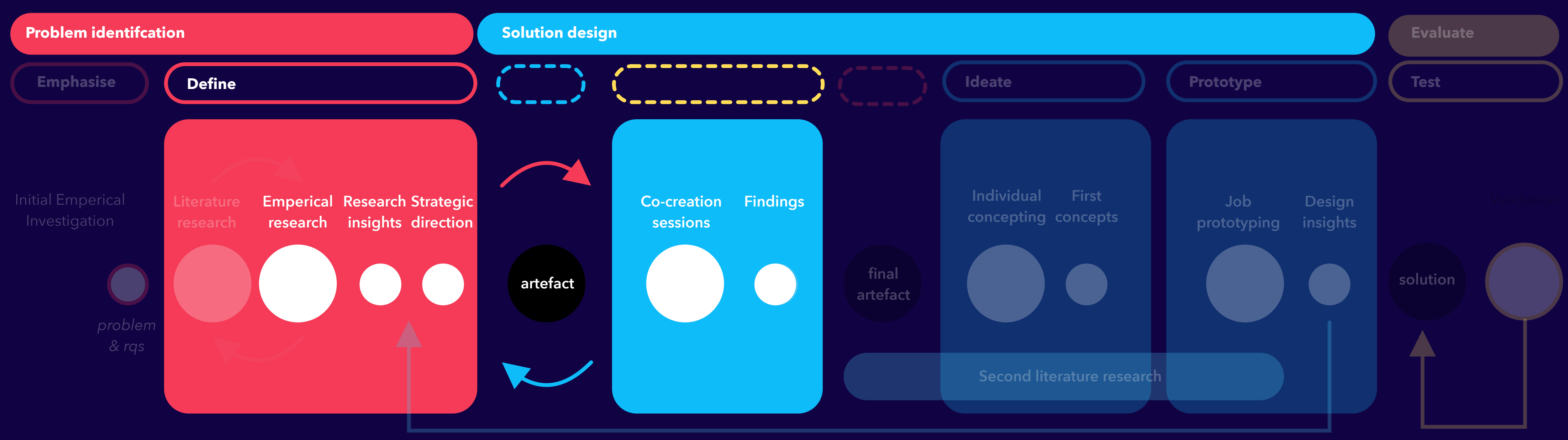
How can this data-design integration be facilitated in digital consulting firms?

Figure 2.13 - The thesis two research questions.

3. Company research

This chapter discusses the empirical research findings. The first subchapter discusses the three-step empirical research approach. The discussion of the research findings is divided into three subchapters, the organisation, data design integration and facilitation. The chapter concludes with a synthesis and provides a strategic direction for the DCF.

3.1 Research set up
3.2 Organisation
3.3 Data design integration
3.4 Facilitation
3.5 Problematization



3.1 Emperical research setup

Based on the initial empirical investigation and the literature review, the need for empirical research in the data-design field is withdrawn. A 5-month empirical research study is performed with a DCF (introduced in p. 10.) The study aims to research four foci; organisational context, data-design integration, data-design collaboration and data-design facilitation. In table 3.1, the subcategories, objective and protocol of the foci are elaborated.

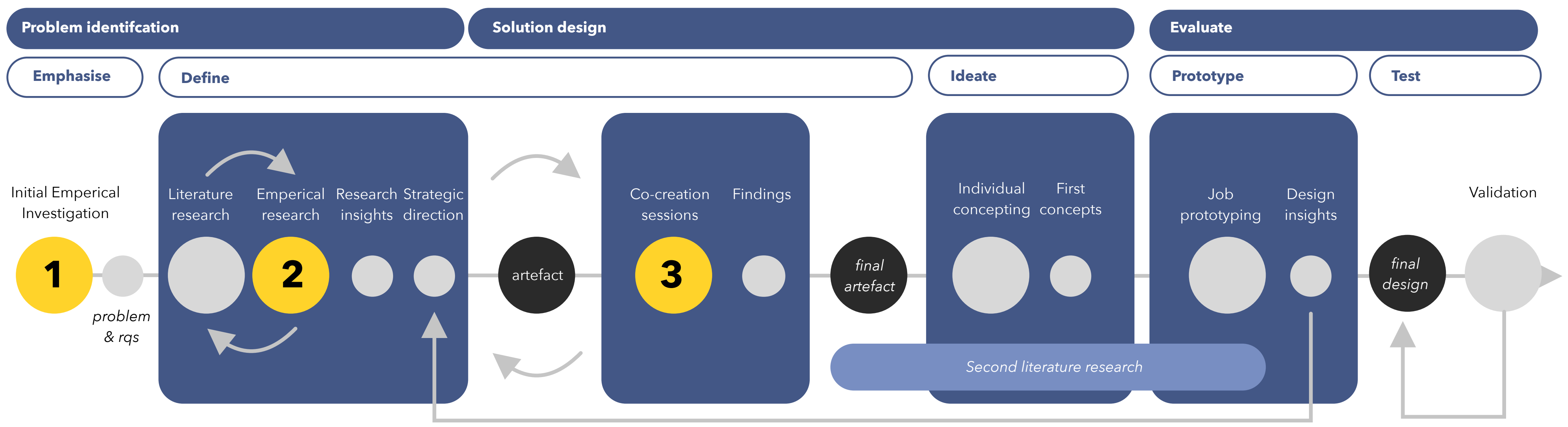
Foci	Subcategories	Objective of analysis	Protocol
Organisational context	Business strategy, consulting model, products and services, operating context (client and market) and organisational elements; people, culture, structure, processes, systems, performance measures.	Understanding the practical context of digital consulting firms in order to understand the influence of this context on the data-design collaboration	Synthesis between primary - interviews, observations and secondary - market analysis, future scenario mapping trend analysis.
Data-design integration	Data science and design innovation	In-depth understanding how what the main opportunity for DCFs is to integrate the two disciplines	
Data design collaboration	Data science team / data scientist and design team / designers.	Discovering in-depth insights/guidelines/issues for collaboration between data scientist and designers in the DCF's practical context	Stakeholder mapping, ersonas
Facilitation	Knowledge, knowledge management, learning and innovation	In-depth understanding how a new collaboration or opportunity can be implemented in a digital consulting firm.	Customer journey mapping

Table 3.1 - Foci of emperical reseach, subcategories, objective and protocol

3.1.1 Process

The empirical research process consists of a three-step approach, visualised in figure 3.2. The first step aims to bring a deeper understanding of the foci in the practical context of the DCF. On the insights from the initial empirical investigation and the knowledge base developed in the literature review, employees are interviewed. In practice, the literature and empirical research are more iteratively performed to provide scope continuously. Based on a thematic analysis, critical findings are drafted from a research and a strategic direction perspective.

Figure 3.2 - Three step emperical research process



In the second step, an artefact is designed based on critical research insights and strategic direction. This artefact allows visualising these "in a socially recognisable form" (Orlikowski and Iacono 2001, p. 121). The third step aims to evaluate and further develop the artefact. Orlikowski and Iacono argue that although the artefact is often theory ingrained, it allows it to be subjected to the organisational practice, evaluation and further improvements.

3.1.2 Methods

During the initial empirical investigation, a total of 19 interviews are performed. Unstructured interviews are used to expose unanticipated themes and better understand the employees' social reality from their perspective (Zhang and Wildemuth, 2009). The purpose of this activity is theory development rather than theory testing, and no hypothesis should be developed beforehand (Denzin,1989; Robertson & Boyle, 1984). Figure 3.2.1 provides an overview of the different interview methods used in the emperical research.

During the second part of the empirical research, a total of 24 interviews are performed. Semi-structured are used as the primary inquiry technique. Semi-structured interviews are well suited when a researcher wants to explore a particular topic in-depth and maintain flexibility to probe to thoroughly understand the answers provided (Harrel and Bradley, 2009). An interview guide is prepared, the questions are standardized and open ended. This allows to compare the interview findings while maintaining an open discussion that allows probing the participants. After the interviews are analysed, validation interviews are used to increase the validity of the findings; the participants are asked to provide feedback on the analysis findings (Golafshani, 2003).

	initial emperical investigation		emperical research			
	Exploratory interviews (unstructured)	Expert interviews (semi-structured)	1nd round interviews (semi-structured)	Validation interviews (co-reflection)	2nd round interviews (semi-structured)	Co-creation workshop (observations)
design (innovation)	5*	2 - Phd'er and data-design expert	4*	4*	3	2
data science	4*	2	3*	1*	2	1
strategy consulting	2*				2	1*
other	1 - director DCF	2 - Phd'er organisation design & director external consultatn	4 - Innovation managers DCF's client organisations		1 - HR manager at DCF	2 - Retail industry lead & data-design experts (Phillips)

Figure 3.2.1 - Participant during emperical research - per phase, activity and discipline

To evaluate the artefact in practical context, observation is used as inquiry techniques. Observations are more applicable to uncover a better understanding of the interactions between a group (Kumar, 2011). In contrast to interviews (that uncover explicit knowledge like what people say and think), observations allow us to uncover more profound knowledge of what people do during use (Frouke Sleeswijk Visser, 2005).

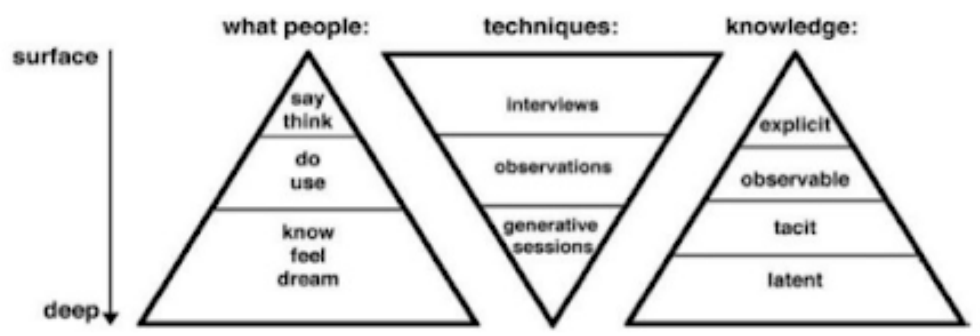


Figure 3.3 - Four levels of knowledge, from surface to deep understanding from Frouke Sleeswijk Visser, 2005

Sampling

The participants are purposefully selected. Figure 3.4 provides an overview of the selected interviewees. The interviewees can be divided into four subgroups; design innovation, data science, strategy consulting and others. During the semi-structured interviews, the participants are selected based on two criteria; During the initial empirical research, friction is found between the data scientist and designers. For that reason, employees from these two teams are selected. From both teams, the team lead is included to provide a holistic view and compare the data (is there any difference found because of the position the employees have). Two principles determined the number of participants selected; saturation and availability. The participants of the client interviews are selected on three criteria. First, all interviewees are selected from one industry to allow comparability between the findings. The retail sector is identified with the DCFs management as strategically promising. Second, the interviewee should have a position as (or similar to) innovation manager. Last. The interviewees are all intended to be positions in a different enterprise size, ranging from small, medium and large enterprises) to allow a holistic perspective of the DCFs clients. The interviewees from the second round of semi-structured interviews are selected based on initial results from the analysis to provide information on knowledge gaps, the contradiction between data findings, or to explore fruitful strategic directions in depth.

3.1.3 Procedure

The unstructured exploratory interviews are performed between half an hour and an hour. These interviews are partly performed face-to-face and partly online video calls due to the COVID-19 outbreak. The 1-hour semi-structured interviews (both internal as the client - in the first round as the second round) are conducted via video call and are audio recorded. The semi-structured interviews consist of three parts; a project introduction, the review of a prepared assignment by the interviewees and semi-structured questions. The interviews are audio recorded notes taken. The 1-hour validation interviews are performed via video call and are performed with the use of an online tool - Mural. This allowed us to present the findings in a clear view and write feedback down.

In order to evaluate the designed artefact in the DCFs practical context, a sprint week is performed including two online co-creation sessions. Table 1 provides an overview of the activities, the goal, the input and the participants. Between each step, the results of each activity are further concepted and used in the following workshops. In appendix 3.6, a more elaborate overview is provided on the activities performed and the individual results. During these workshops, the researcher was the facilitator of the co-creation workshops. The client validation is not performed, as the workshop results did not lead to valuable output (see chapter 3.4.2 artefact creation and evaluation).

Part of study	Participants	Context
Case development	retail industry growth lead	Prior to the workshops, a use case is developed during a one hour session with the DCFs retail industry growth lead
Proposition workshop	service designer 1 data scientist	Digital co-creation session in order to develop a proposition based on the developed use case
Process workshop	service designer 2 data scientist external expert data-designer Phillips)	Digital co-creation session in order to develop a way of working under the proposition workshop
Demo client validation	-	Based on workshop findings, demo is developed to be evaluated with client to test product market fit of proposition

Table 3.2 - Four steps of the artefact validation

3.1.4 Data analysis

The interview's audio transcripts are listened back to and together with the notes from the observer quotes are transcribed. An thematic analysis is chosen for the data analysis. A thematic analysis refers to identifying, analysing and interpreting patterns of meaning (ie. themes) (Braun & Clarke, 2006). The development of understanding of the themes is supported by the DIKW development, see figure 3.3.1 (Sanders an Stappers, 2010. The categorising is based on the transcribed quotes and is iterated multiple times to find patterns and gather insights related to the foci. In addition, the findings are compared to secondary data sources (i.e. the literature insights, trend analysis and internal company documents). This allows to identify similarities, contradictions or possible missings gaps of knowledge.

In addition, two methods are used to increase the understanding of the data; the theory of constraints (Goldratt, 1984) and validation sessions with employees. Goldratt's theory of constraints is applied to find the dynamic between individual data findings and identify potential root causes for the data-design integration issues. This activity resulted in clusters of barriers and the inter dynamics between them (see Appendix 3.4). To validate the clusters of barriers, interviews with employees are performed. Based on the insights from the validation interviews, the findings are improved.

In particular, the last step provided many insights towards the strategic direction the design phase should aim to solve. The three methods were not linearly used but rather as an iterative process to constantly reinforce each other. In the second step, the audio transcripts are listened back to and synthesised with the author's observations. The findings of this analysis are synthesised with the thematic clusters from the initial step.

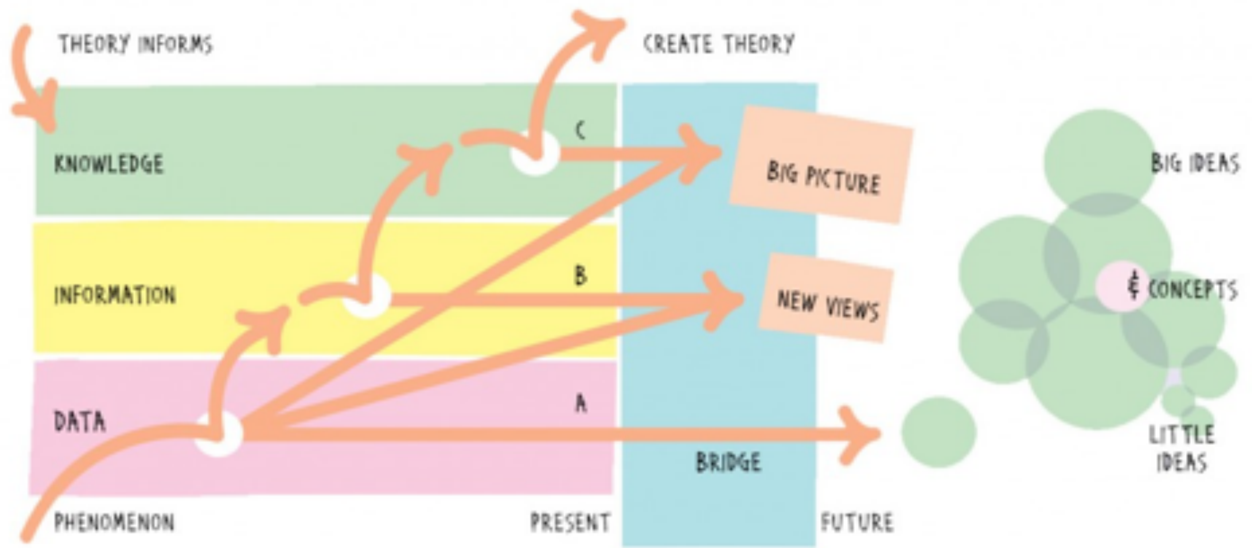


Figure 3.3.1 - DIKW in relation to thematic clustering. from, Analysis of data by Sanders and Stappers (2012), based on the theory of Ackoff's DIKW scheme. Sanders, E. B.-N., and Stappers, P. J. Convivial Toolbox: Generative Research for the Front End of Design. BIS Publishers, 2012.

3.2 Organisational context

This subchapter provides the research findings from the organisational perspective and data science- and design service offerings. First, an overview is provided of the DCF's economic consulting model, organisation structure, culture and processes. Second, the DCFs client offerings and approaches to design innovation and data science are discussed.

3.2.1 Organisation

This section aims to provide a better understanding of the organisational view of the DCF. To restate the DCFs strategic direction is the growth towards large enterprises.

Expert economic model

The DCF's economic model can be classified as 'expert economics' (Hansen et al., 1999). This model implies that the firms' service offerings are highly customised for each project to solve client's unique challenges. Concerning the business model, the project initially fixed budgets are calculated on consultants' hourly fees but tend to be sold with 'milestones' (go-no-go moments for the client can decide to continue the project based on the preliminary outcomes). This business model implies the length of projects as revenue drivers and the number of projects and hourly fee. The most significant cost driver for the firm is employee salary.

DCFs organisation structure - matrix

The DCF has recently implemented a matrix organisation structure (Stanford, 2007). Management argues the need to support the growth strategy towards enterprises and maintain the customisation of service offerings. A matrix structure is a commonly used structure among consulting firms. Due to project-based work, the flexibility in service offerings these projects require and increase a firm's ability to rapidly respond to acquired projects (Sy and Cote, 2004). A matrix structure places a companies' internal functions (i.e. the data science and design teams) across the project function. Figure 3.4 visualises the DCF's organisation structure - horizontal the expertise teams (or functions) across new-formed 'industry teams'. These industry teams are responsible for the firm's growth in a specific industry. Employees in these teams have an ongoing conversation with client accounts and acquire projects based on client needs during these conversations.

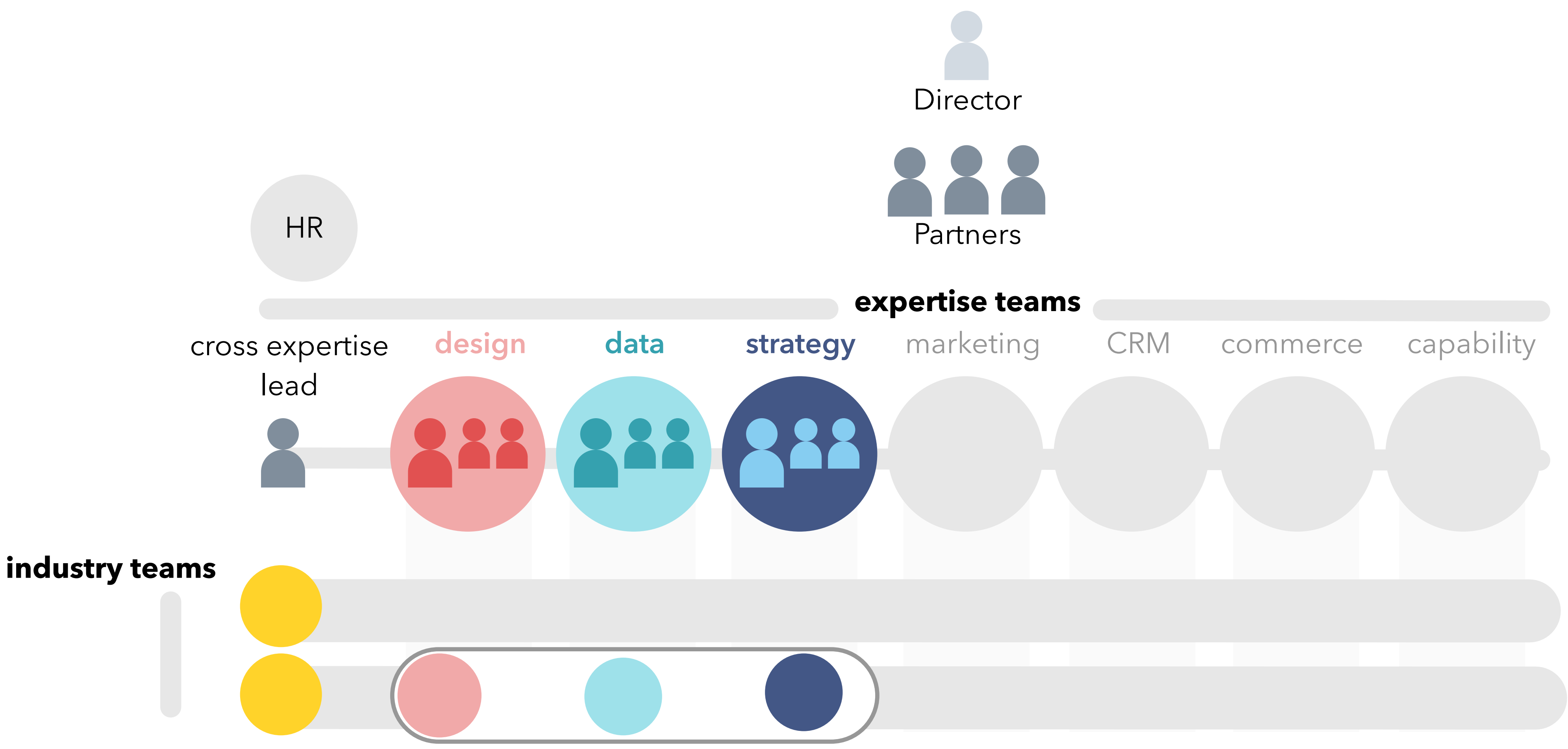


Figure 3.4 - Organisation structure DCF - matrix - expertise teams cross from industry teams

Culture and processes

The DCFs culture can be typified as pragmatic. Much of the firm's differentiation comes from this pragmatic stance. Management argues that by providing clients with solutions driven projects, the firm can differentiate itself from larger consultants. According to DCF's director, 'in previous years this agility has been one of the main drivers of the organisation's growth. This culture expresses in the DCFs processes, which can be typified as ad hoc. Elaborated by one of the firms' industry team's lead, 'nobody in our company likes sticky processes'.

Design innovation

The DCFs service offerings to design innovation is based on a collaborative approach between strategy consulting and design (further consists of both service design and UX/UI design). The role of each team in the innovation offering can be viewed from a viability, desirability and feasibility perspective. The strategy team provides viability, for example, in the form of a business case. For example, the design team provides desirability by customer research or the development of new value propositions.

From a more process perspective, the five-stage innovation process (see figure 3.5) tends to be initiated by the strategy team - in the form of a strategic direction 'where to play. The service design team follows this strategic direction - and creates a value proposition 'what to offer, to whom'. Figure 3.6 visualises the design process based on an example case. This 5-step approach is similar to the Double Diamond approach (UK Design Council, 2004). Based on the developed propostion, UX design create a concept. After the last milestone, the innovation project is transferred to the industry teams (see figure 3.4). These teams further developed and scale the innovation internally at clients. The design is not involved in this latter phase and thus is out of the scope.

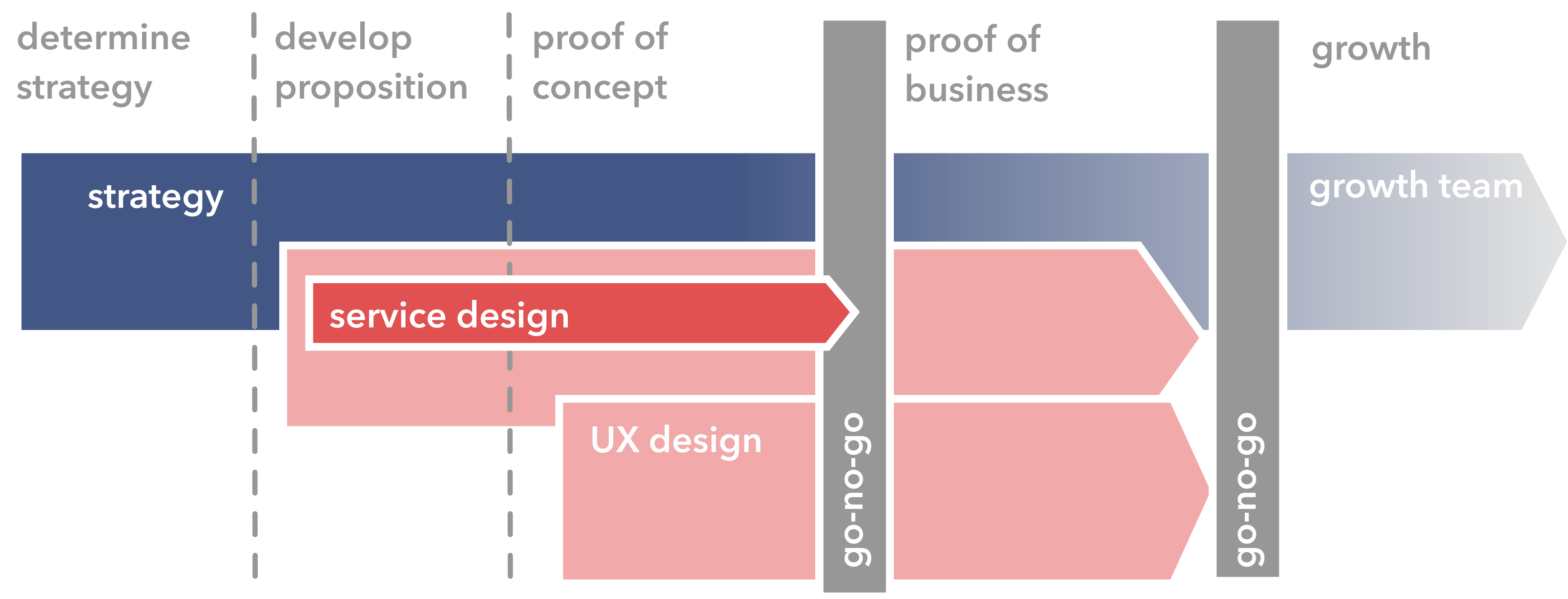


Figure 3.5 - Multidisciplinary Innovation process DCF

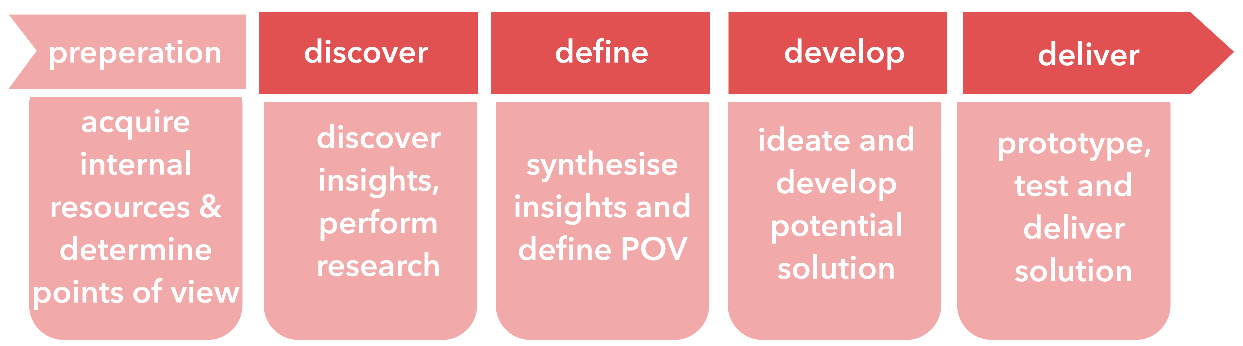


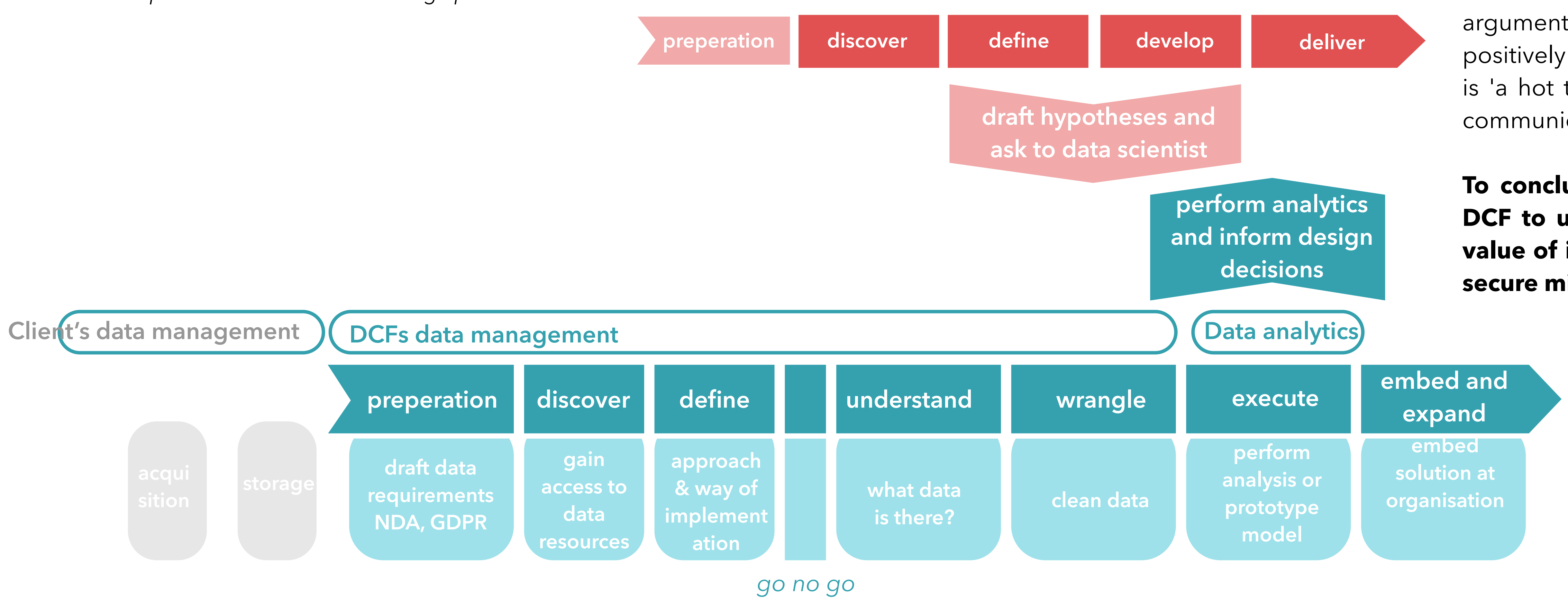
Figure 3.6 - DCF design team's project approach - example of value propostion project with sprint week. Based on design thinking double daimond Double Diamond (UK Design Council, 2004).

Data science - how does DCFs approach data science?
The firm's data team's primary service offering is the development of 'data solutions to clients. A data solution refers to automated algorithms that are embedded in the client's internal IT infrastructure. These data solutions aim to provide the clients with continuous data insights for data-driven decision making. Examples of these offerings are customer lifetime value modelling, price and order forecasting or buying behaviour insights. A secondary offering is the support of DCFs internal teams in developing their solutions. An example is supported on strategy consulting projects, where the data scientist performs analytics to provide arguments for the developed client strategy.

The data science teams' process (figure 3.7) consists of seven steps with one stage-gate. The process of data science differs from the theoretical 'big data processes' (Gandomi and Haider, 2015) provided in the literature review on two points. First, there are two data management processes, one at the client and one internally at the DCF. The data has to be transferred from the client to the DCFs internal data infrastructure. Second, before any data transfer can be made from the client to the DCF, legal contracts must be signed. These activities differ from data science analytics at other organisations and cause many technical and legal issues.

"keeping it simple, laying different data sources over each other, finding the right insights and visualising that simple. That is what is now needed for impacting organisations"
- data designer

Figure 3.7 - Data science process & Data informed design process



3.3 Data-design integration

This subchapter elaborates the research findings regarding the integration of data science in design innovation. First, the foremost opportunity of data-informed design is discussed and the value it can provide for stakeholders. Second, the practical issues of the data-design integration are discussed.

3.3.1 Opportunity - data-informed design innovation
Data-informed design innovation is currently the foremost opportunity for the DCF to use data science in design innovation client projects. This is concluded from the analyzing case studies and is validated by internal data experts. First, the use of data science in the design team is currently immature. According to one of the data scientists, the DCF 'should first focus on getting the basics right. Based on the interviews, a maturity roadmap is suggested. To restate the scope taken in this research, the integration of data science in design innovation implies that data visualization is out of scope.

Data-informed design innovation refers to the approach where big data and analytics are used to drive design innovation decisions, alongside other more qualitative sources like user research or market analysis (King and Churchill, 2017). A simplified process of visualization in figure 3.7. During data-informed design innovation, designers and strategy consultants draft concrete assumptions or hypotheses about certain possible design decisions and share these with the data scientist. Data scientists can perform business analytics, primarily with the client's internal data to provide information. In general, three kinds of information can be provided by the data science team (1) The behaviour of the client's consumers, for example, customer segmentation (2) The behaviour of the client's business, for example, sales reports (3) External data insights like market analyses.

Perceived value stakeholders
Concluded from the thematic clustering, the interviewees perceive the value of data-informed design (and thus successfully integrating data science and design innovation) on three levels; improve quality of innovations, secure milestones and proposition development. First, by broadening the number of information decisions are based upon, the interviewees perceive an increase in the chance that these crucial decisions turn out to be correct. This increase in 'right' decisions increases the success chance of the innovation itself, which is directly beneficial for the clients. This is also indirectly beneficial for the DCF as it increases the client's satisfaction and client retention rate. A more direct benefit is decreasing the client's perceived risk during go-no go moments. By proving better argumentation for design innovation decisions, clients continue projects longer. The DCFs revenue is positively related to the length of projects. Last, the interviewees suggest that data science currently is 'a hot topic'. Strengthening the current design innovation propositions with data science allows communication to clients and increases the ability to acquire projects.

To conclude, data-informed design innovation is currently the foremost opportunity for the DCF to use data science in design innovation client projects. The interviewees perceive the value of integrating data science and design innovation to improve the quality of innovations, secure milestones and proposition development.

"quantitative data was always important to inform business decisions as innovation, but now knowing better how your clients behave digitally, data is becoming one-hundered percent more valuable"
- Interviewee - innovation manager client DCF

"Nobody in our company likes sticky processes, but that is also our pitfall"
- strategy lead during interview

3.3.2. Practical issues

Concluded from the initial empirical investigation, the DCF has issues integrating its data science and design team. In this section, the empirical research findings regarding the practical issues for data-design integration are discussed. The issues are categorized into three layers - organization context, client interaction and collaboration.

Organization perspective

Silos - The expert economic model and the matrix organization structure bring two interpersonal issues regarding the data-design integration; a multidisciplinary approach with silo-focussed employees and team forming decisions. First, employees tend to focus on their discipline. Although team members recognize the importance of contribution from other disciplines, both teams do individual client needs, separate offering development, separate opportunity exploitations, and employees are developed independently (Nicholson and Armitage, 2000). These results argue that the DFCs approach is multidisciplinary. Second, the introduction of 'industry teams' implicate project acquisition and expert teams are separated. Without being up-to-date on the service offerings (and in specific data-informed design projects), these are not communicated to clients and thus constraint any projects from taking place.

Ad hoc processes - The pragmatic culture has a constraining influence on data-design integration. Although this pragmatism supports the organization's agility and rapidly responds to context changes, this pragmatic culture also results in 'ad hoc processes and a lack of formalization. To conclude, there are no processes in place to support cross-functional learning, communication and knowledge sharing.

Client Interaction

Client budget constraints - Based on the analysis of client interviews, it can be concluded that the client's profile highly determines performing data-informed design innovation projects (see 3.8). According to the DCFs design lead, 'the biggest constraint for integrating data science in design innovation is the client's project budget'. Adding data science to a design innovation project increases the project's price (directly based on hour fee). Without adequately communicating the clients perceived ROI (i.e. return on investment), clients tend to choose not to include data science.

"The biggest constraint for data-design projects is the client's budget"
- design lead during interview

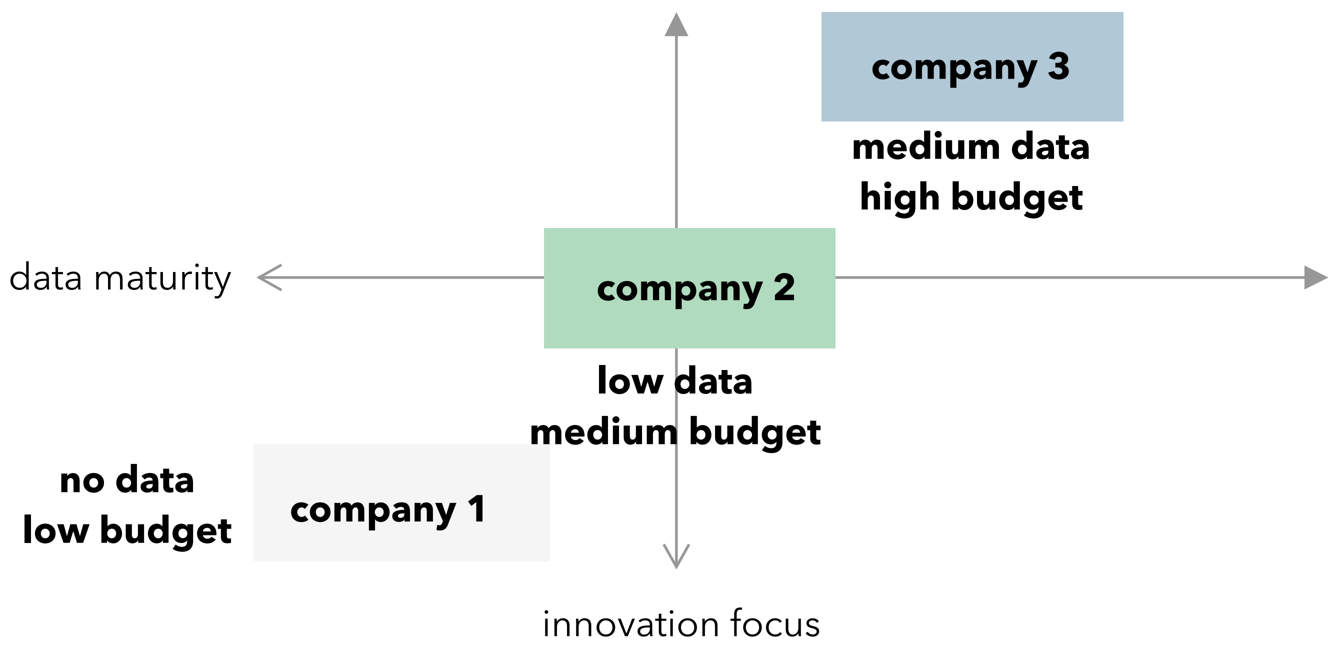


Figure 3.8 - Retail segments - three company segments based on data maturity and innovation focus

"The largest project constraint for data projects is data availability, accessibility and affordability"
- data lead during interview

"Knock-outs constraint the possibility of using data, like technical stuff that the data is not present"
- design lead during interview

Data constraints - In contrast to design innovation projects, data-informed design innovation projects are constrained by the data availability, accessibility and affordability to perform analytics. Availability refers to the amount of valuable and useful data available to perform (quality) analytics. Accessibility refers to the access DCF's data scientists have to the client's data resources. Last, affordability refers to the costs that are needed to acquire, clean and run the data. In practice, regulations (GDPR) and technical issues cause high effort in acquiring the needed data. External data sources can be used but are too expensive to acquire for clients in many cases. Compared to a design innovation process, the first three phases of the data science journey are focused on determining, locating, acquiring and cleaning the data. These findings suggest that in practice, data design innovation projects demand higher resources and are much more constrained by practical limitations than design innovation projects.

Collaboration between data scientist and designers

Difficult to establish synergy - Establishing synergy during data-design collaborations is found to be complicated. Concluded from research, on many occasions, the findings of the data and design teams do not match. During a client project (aiming to personalize an email system), one of the design team's developed personas was triggered by images of experiential trips. While the data segmentation, in theory, is based on the same set of customers, there are no metrics for 'experiential trips' This increased the complexity of the work and decreased the quality of the delivered solution. Without predetermining the precise level of metric that aims to be combined with design insights, the two data insights will be too far apart.

Difference in culture - Two differences in culture are found from research, the needed levels of concreteness and reasoning approach (see figure 3.9). First, while designers thrive on insecurity, ambiguity and 'wicked challenges', data scientists are trained to stay away from these dangers. As explained by a data scientist, 'during university, any insecurity is kicked out of it, as we cannot prove any value otherwise'. Second, while designers tend to have an abductive way of reasoning (what else is there to inspire and is that think possible as a solution?), data scientists have an inductive and deductive way of reasoning (how can I prove this to make my next step smaller to solve). Without better understanding each other's crafts, the chances of successful collaborations are low.

"client safari, now we are going broader again? We are actually untaught that, because back in the day we were tapped on the finger, because then we lose grip. How can I prove value then? "
- data scientist during collaborative meeting

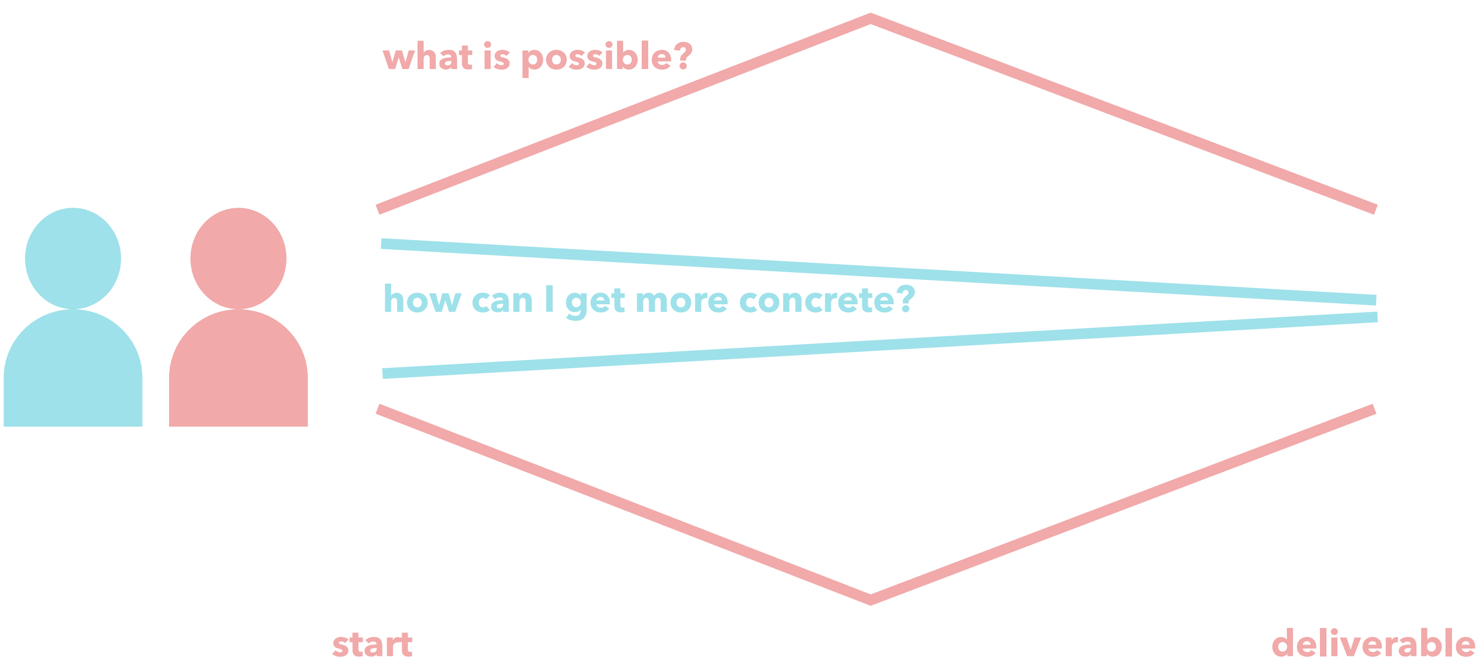


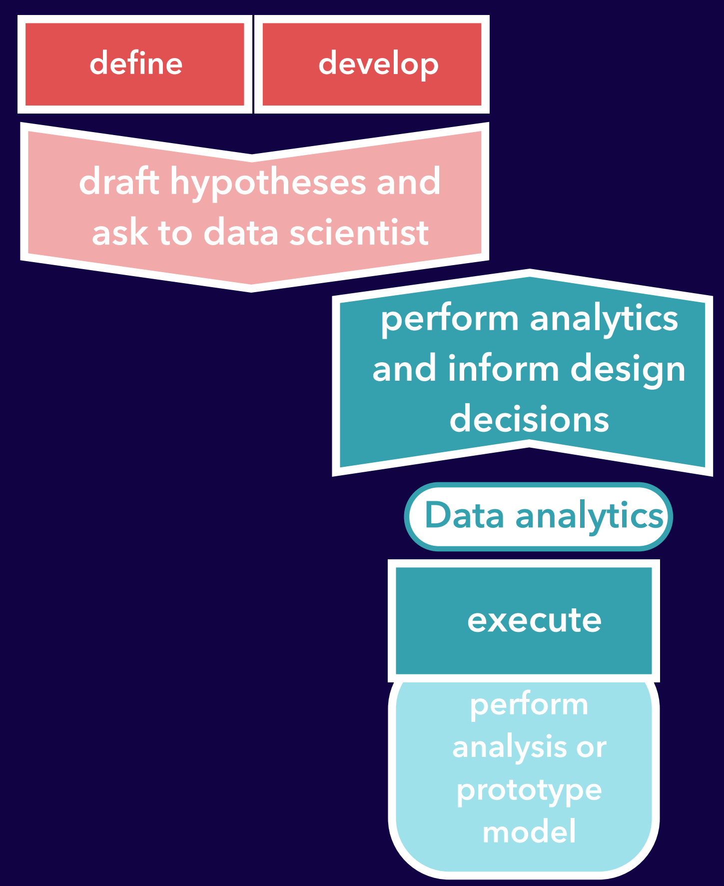
Figure 3.9 - Issue culture - difference in project approach, mindset and level of granularity

Conclusions subchapter 3.3

Data-informed design innovation is currently the foremost opportunity for integration. Designers and strategy consultants draft concrete assumptions or hypotheses about certain possible design decisions and share these with the data scientist. Data scientists can perform business analytics in order to provide answers to these. Employees perceive the value of integrating data science and design innovation to improve the quality of innovations, secure milestones and proposition development.

However, the DCF's current approach to data-design innovation is multidisciplinary. The integration of and collaboration between the data and design team is found to be problematic. Concluded from empirical research, six practical issues are identified. Below these issues are visualised.

Opportunity - data-informed design



Practical constraints

3.4 Facilitation

This section discusses the findings of the empirical research regarding the facilitation of the data-design integration. First, the findings regarding the firm's knowledge and learning systems are discussed. Second, the design and evaluation of an artefact are discussed, aiming to facilitate the firm's learning system. Based on the synthesis of all research findings, the subchapter is concluded with the recommended learning strategy.

3.4.1 Issues in information system

This section elaborates the findings from the empirical research regarding the DCF's knowledge and learning system. The firm's management emphasises that knowledge should mainly be acquired by performing projects. However, this means that most knowledge in the organisation stays at an individual and on a tacit level. The framework for organisational learning is used from the literature review (figure 3.9) to understand the issues for data-design integration.

Knowledge base

From the validation interviews, a lack of knowledge is found. First, the data and design team miss an understanding of the other disciplines. According to a designer, 'we [design team] do not know when to ask the other team on board. Another designer further elaborates, 'I do not know which questions to ask the data scientist'. The data science team tends not to understand what design does and focus on only asking for, e.g. making slides more beautiful This lack of knowledge increases fiction and lowers the ability to collaborate.

Knowledge management

Although both the data and design team activity share knowledge during team meetings, this does not cross-functional. Learnings of projects are not actively shared amongst the organisation. This lack of knowledge management causes a lack of internal awareness of the potential between both teams and leads to non-communication to clients. The analysis suggests that this is due mainly to the lack of management support. Management is mainly focused on revenue and 'billability'. One of the designers elaborates, 'sometimes I feel like the billability monster chases me'.

Innovation on knowledge - chicken and egg problem

The DCF tends to rely on the use of present knowledge directly for competitive advantage rather than innovation. In addition, the firm tends to be reactive to current customers needs rather than developing new service offerings that could be interesting. According to a strategy consultant, 'rarely any innovation happens internally in the firm itself'. This suggests a lack of knowledge-based sustainable competitive advantage.

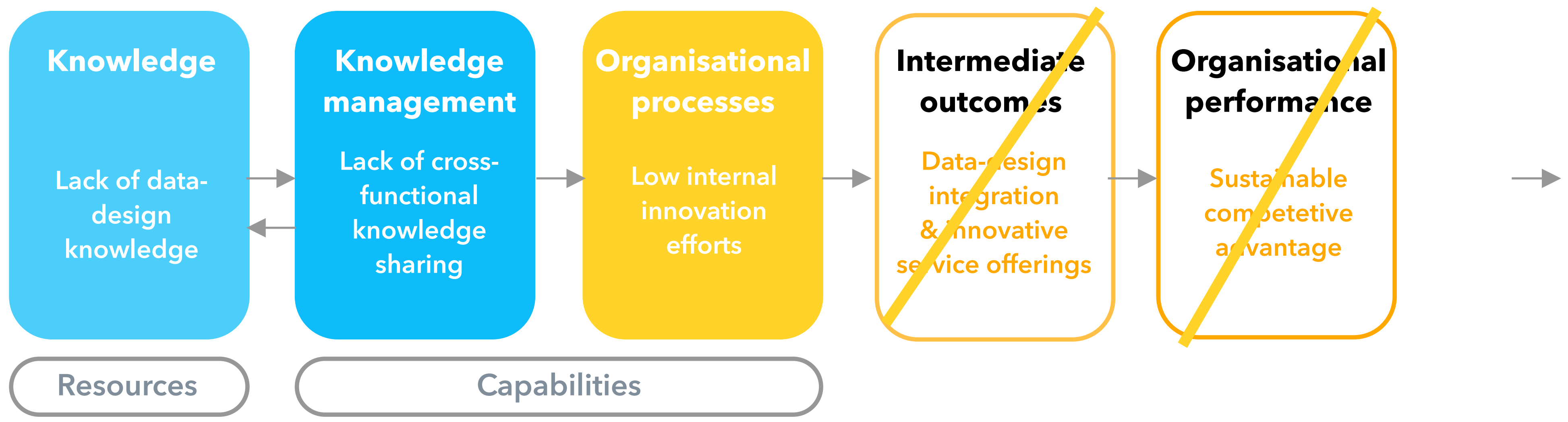


Figure 3.9 - Initial assumed issues in the DCFs information system, framework adapted from King (2009) and Zubac et al., (2010)

To conclude, the DCF has three issues regarding the facilitation of the integration of data science in design innovation; lack of knowledge regarding data design innovation, lack of cross-functional knowledge sharing and lack of knowledge for innovation. These three issues suggest that the firm cannot sustain a knowledge-based sustainable competitive advantage concerning the DCF growth strategy for relevance to large enterprises. Based on these findings, the firm is currently not able to integrate the two teams. This is problematic because this constrains the firm from developing data design innovation service offerings necessary to stay relevant to enterprises.

Figure 3.10 - Build phase of the artefact - framework for learning

3.4.2 Artefact

To support the DCF's information systems, an artefact is designed (see Appendix 3.5). This design is based on the synthesis of the practical integration issues from chapter 3.3.2 and the facilitation issues from the previous section. The design is a learning system framework. In figure 3.10, a simplified version of the four-step build phase of the framework is visualised. The primary value assumption behind the framework is that "the integration of data science in design innovation can be facilitated by providing the DCF's designers and data scientists; (1) a framework for learning that (2) addresses current knowledge gaps and (3) develops innovative service offerings".

To evaluate the artefact, a sprint week including two 2-hour co-creation workshops with the DCFs data scientists and designers is designed and performed (see chapter 3.1.2 for a more elaborated procedure). Concluded from the evaluation, the central value hypothesis of the framework was invalidated. Generating the right knowledge in the right way does not enable integration between the DCF's data and design team. Appendix X provides a more in-depth discussion of the findings. The analysis suggests it is rather about using (or lack of using) knowledge during decision-making, which enables (or constraints) collaboration between the design and data team.

The findings suggest that knowledge is not perse missing but is not made available to decision-makers at decision moments. In addition, the practical value of knowledge should not be to *learn how to collaborate* but rather to *allow collaborations to happen*. To conclude, in addition to knowledge management and learning, decision making facilitates the integration of data science in design innovation by allowing collaboration to happen.

3.4.3 Customer journey mapping

To better understand the influence of the DCF's decision-making process on the data-design integration, customer journey mapping (CJM) is performed. CJM refers to a design activity that aims to map a customers (or, in this case, employee's) interactions, goals, emotions and barriers throughout the use of a product (Abbing, 2010). Figure 3.11 provides a simplified visualisation of the result - a 6 step project journey. Appendix 3.7 provides the procedure and the complete customer journey map. Concluded from CJM, the employees identified two pain points that constraint the data-design integration; pre-proposal and proposal.

Pain point 1 - pre-proposal
During the pre-proposal step, employees of the industry teams are not well informed of the data and design team's service offerings. According to one of the firm's designers, 'we really depend on the input from the growth-leads' The lack of information results in either missed opportunities or pre-proposal that do not reflect actual service offerings.

Pain point 2 - proposal
After the pre-proposal, the data science and design teams aim to offer a more detailed proposal tailored to the specific needs (often on a misjudged pre-proposal). During this process, decision-makers are not critical of the project constraints, resulting in inaccurate planning of resources that lead to under-delivery of clients or overhead costs during collaboration.

"2 of the 3 project failures were about not preparing project well"
- service designer during customer journey mapping

Figure 3.11 - Project cycle - two pain points; pre-proposal and proposal.

3.5 Strategic direction

The DCF has a growth strategy crucial in order to stay relevant to enterprises. Concluded from the trend analysis, this provides an opportunity and a threat concerning the future of innovation. To stay relevant in the innovation of enterprises, the DCF has to integrate data science in the design innovation approach. The opportunity of data-informed design is identified as the most feasible short opportunity for integration. By synthesising the empirical research findings, evaluating the artefact and customer journey mapping, it is argued that decision making enables the data-design integration. Figure 3.11 provides an overview of the iteration of the learning organisation framework.

Focus - proposal & data and design team's decision makers
The choice is made to focus on the second pain point, the data and the design team's decision-makers during the final proposal development (see figure 3.12). Stated by one of the designers that 'the process should be that the expertise teams are better consulted during these pre-proposal moments'. If both teams on that occasion were consulted, based on the emperical research findings, would still not be able to draft quality proposal together. This suggests that a better way of making decisions should be targeted at the DCF's data and design teams decision-makers.

Learning strategy - personalisation
Based on the findings from the empirical research, it is argued that the DCF needs to use a personalised knowledge strategy to facilitate the integration of data science in design innovation (see figure 3.13). This is based on synthesising four perspectives; organisation, people, information system infrastructure and type of knowledge. From an organisation point of view, the DCF has an expert economic model and therefore needs to emphasise the use of interpersonal networks (Dunford, 2000). From a people point of view, a low commensurability between the data scientist and designers is found (i.e. ease of giving information the same meaning). From an IS infrastructure point of view, prior efforts on codified knowledge have not been found successful. In-team knowledge banks are not in use anymore. Especially regarding cross-discipline knowledge transfer, there is no technological infrastructure. Last, decisions making required diagnoses. Diagnosing is a complex ability that is hard to make explicit and capture by codification (Dunford, 2000).

"Actual working together, in the end is the only way we really are going to integrate"
- data scientist

"We really depends on the quality of the pre-proposals, shit in is shit out"
- service designer during CJM

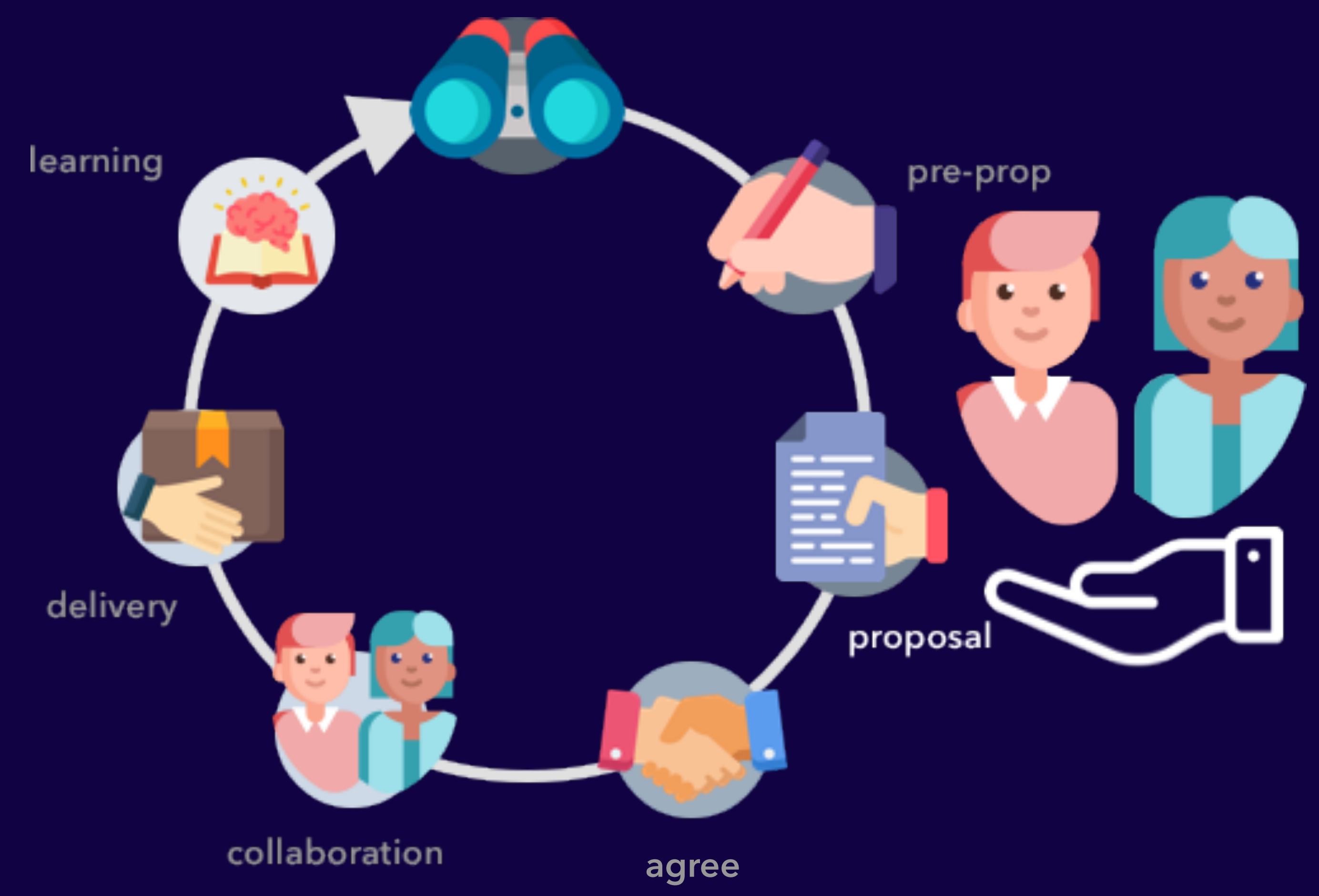


Figure 3.12 - Project cycle - two pain points; pre-proposal and proposal.

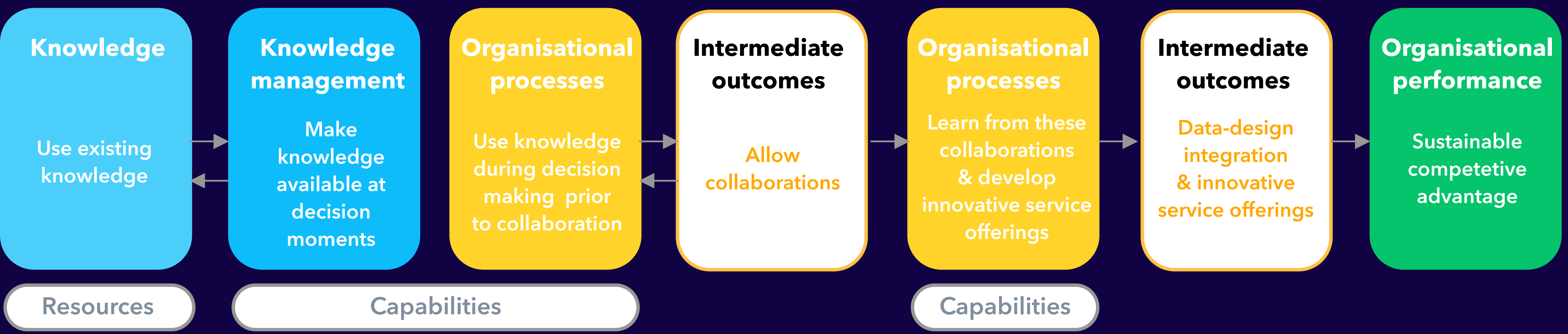


Figure 3.11 - Iteration of assumed issues - allow collaborations by decision making. Framework adapted from King (2009) and Zubac et al., (2010)

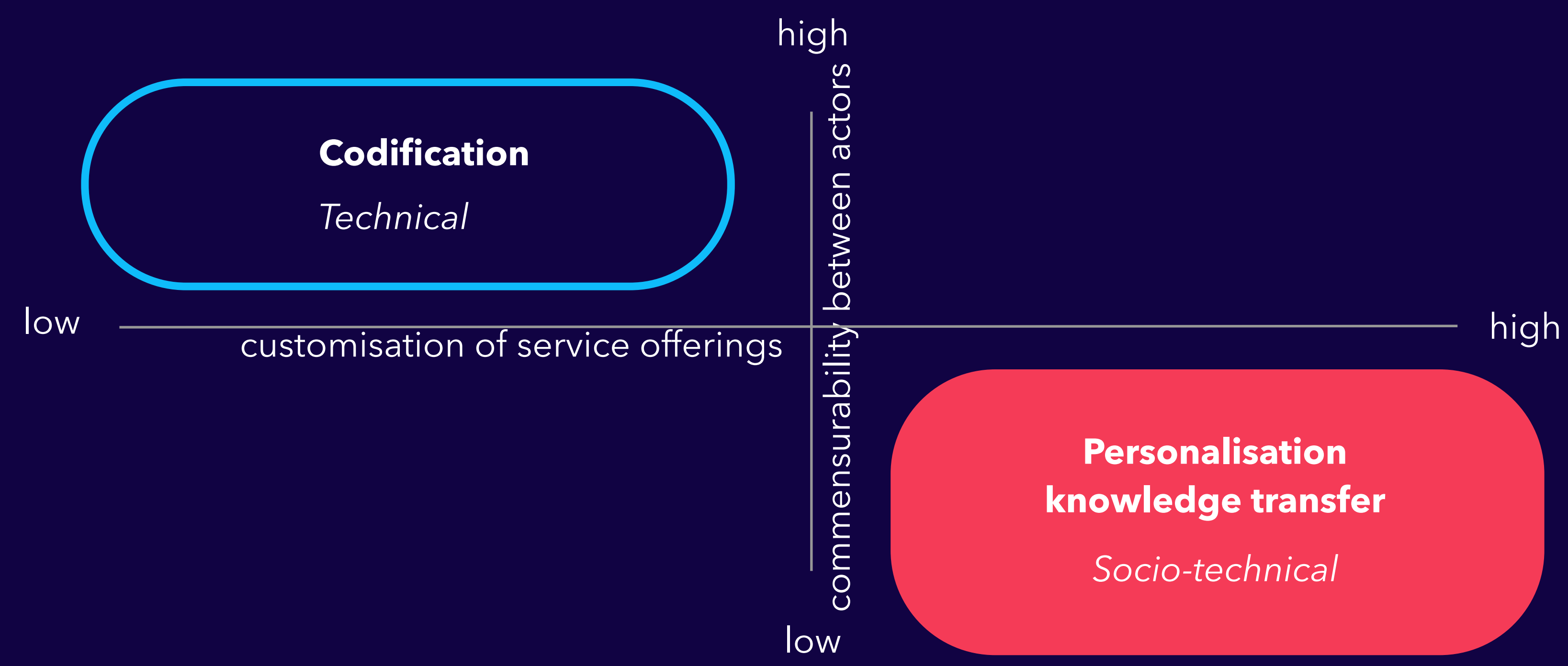


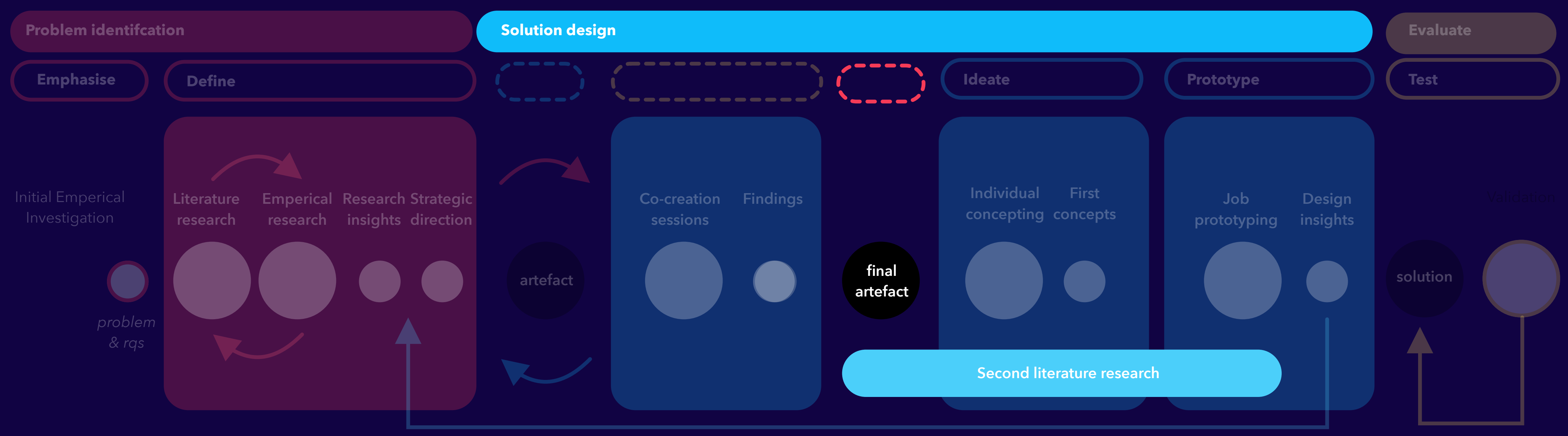
Figure 3.13 - Position of DCF in knowledge transfer strategies, adapted from (Arduin, Grundtstein & Rosenthal Sabroux, 2013) and (Arduin, Grundtstein & Rosenthal Sabroux, 2013).

4. Framework for decision making

This chapter proposed a conceptual framework aimed to support the DCF's data-design integration and facilitation. The framework should be viewed as the bridge between the theoretical realm and the practical realm, i.e. from the design research to designing a solution (Backmen and Barry, 2007).

The first subchapter elaborates the design process and guidelines. Based on these guidelines, the second subchapter proposed the implementation of a new step, internal alignment. The third subchapter proposed a conceptual framework, collaborative decision-making. The chapter concludes with the design challenge and guidelines.

4.1 Design process
4.2 Internal alignment
4.3 Framework
4.4 Design challenge



4.1 Design process

This subchapter discusses the design processes and the design guidelines. The guidelines are based on business insights and aim to solve the strategic problem drafted in chapter 3.4. Based on the strategic direction determined in chapter 3 the framework is developed following the generate test cycle (Simon, 1996). To support the generation of the framework design, an additional literature research is performed emphasising interdisciplinary disciplinary decision making. The 'testing' is conducted in two instances. First, co-reflection is applied during the Define phase. Four online interviews ranging from half an hour to an hour are performed with four service designers. In addition, the framework is also validated during actual use during the final validation study at the end of the research (see chapter 7.2 for findings).

4.1.2 Guidelines from research

Chapter 3 concluded with the set of design requirements to increase the utility of the design for the DCF. This section highlights four of these guidelines, as these essentially underpin the design of the framework: collaborative decision making, a synergy between approaches, align with client's business value and reflect on critical project constraints.

Collaborative decisions: First, as current decision making during the proposal stage is done chiefly individually, the decision process should aim to bring a collaborative approach. The internal experts have to be involved during decision making to ensure the use of quality and up-to-date knowledge. The blue colour presents the data science team and the red the design team.

Synergy between teams: During decision making the data and design teams have to find synergy between their activities and results. Empirical research suggested that synergy is complicated to reach. The teams need to answer three questions during proposal drafting; what are the activities the data and design team will perform? What are the results of these activities? How will we combine these results so that the sum of the parts is greater than the parts?

Align with client's business value: During the proposal draft, the data and design team's decision-makers have to (in addition to technical or customer values) continuously place the client's business value central. As the client budget is one of the most significant constraints, the decision-makers need to have an in-depth understanding of their activities (e.g. adding data science components to design innovation projects) on the client's perceived ROI.

Reflect on project constraints: Last, an emphasis should be put on critical project constraints. This is especially important regarding the data resources (as these have high requirements). Each decision should be critically reflected on; does the project offer the resources I need to perform my activities? Is the data there? Is the data accessible for me? Is the data affordable to prepare for analysis (time and budget)?

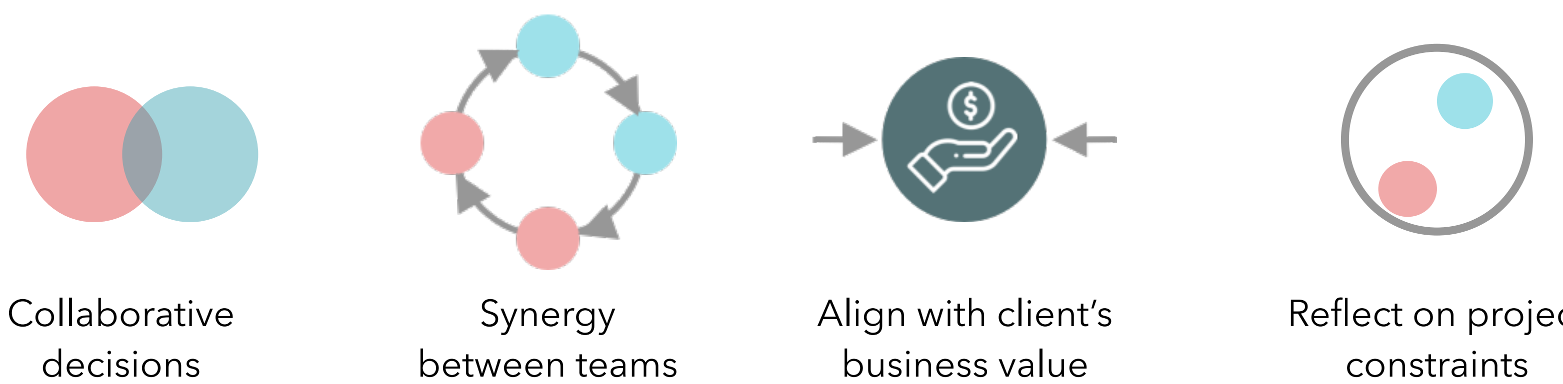


Figure 4.1 - Visual representations of guidelines in framework

4.2 Alignment step

Based on the customer journey mapping and the design requirements, a new step is proposed in the DCFs project journey: internal alignment. This activity aims to enable the DCF's data science and design team's decision-makers to draft valuable data-design proposals that they can communicate to clients. It achieves this by aligning the data and design teams' activities and sub-deliverables while safeguarding the client's business value. Although alignment between the data science and design team is suggested to be important during all interdisciplinary data-design activities, the last chapter argues the proposal drafting step to be the most critical.

Value

Implementing internal alignment during the proposal phase provides the firm value in three ways. First, by making rational collaborative (rather than intuitive and individual) decisions, opportunities for data-design collaboration projects are not missed. These cross-sales drive higher revenue for the DCF. From the teams' perspective, more data-design collaborations allow more on-the-job experience, which is crucial for integrating the teams. Second, by drafting feasible proposals (i.e. in line with actual project constraints like data, time and budget), end solutions have a higher chance of aligning with the proposal. From the perspective of the DCFs clients, the project is in line with expectations. Second, from the standpoint of the DCF, more realistic proposals decrease the risk of unexpected overhead costs, which could harm the margin. Third, create a place for knowledge sharing or 'Ba' (Nonaka and Konno, 1998) the DCF's data and design teams' decision-makers to learn. Because the decision-makers are actively involved in the decision making, the collaborative decision making improves, which in turn leads to more collaboration and thus more learning. To conclude, implementing the collaborative data-design decision framework in the DCF's proposal phase increases data-design collaborations. On-the-job learning drives more revenue from cross-sales, decreases the risk of overhead costs, and provides a place for knowledge transfer.

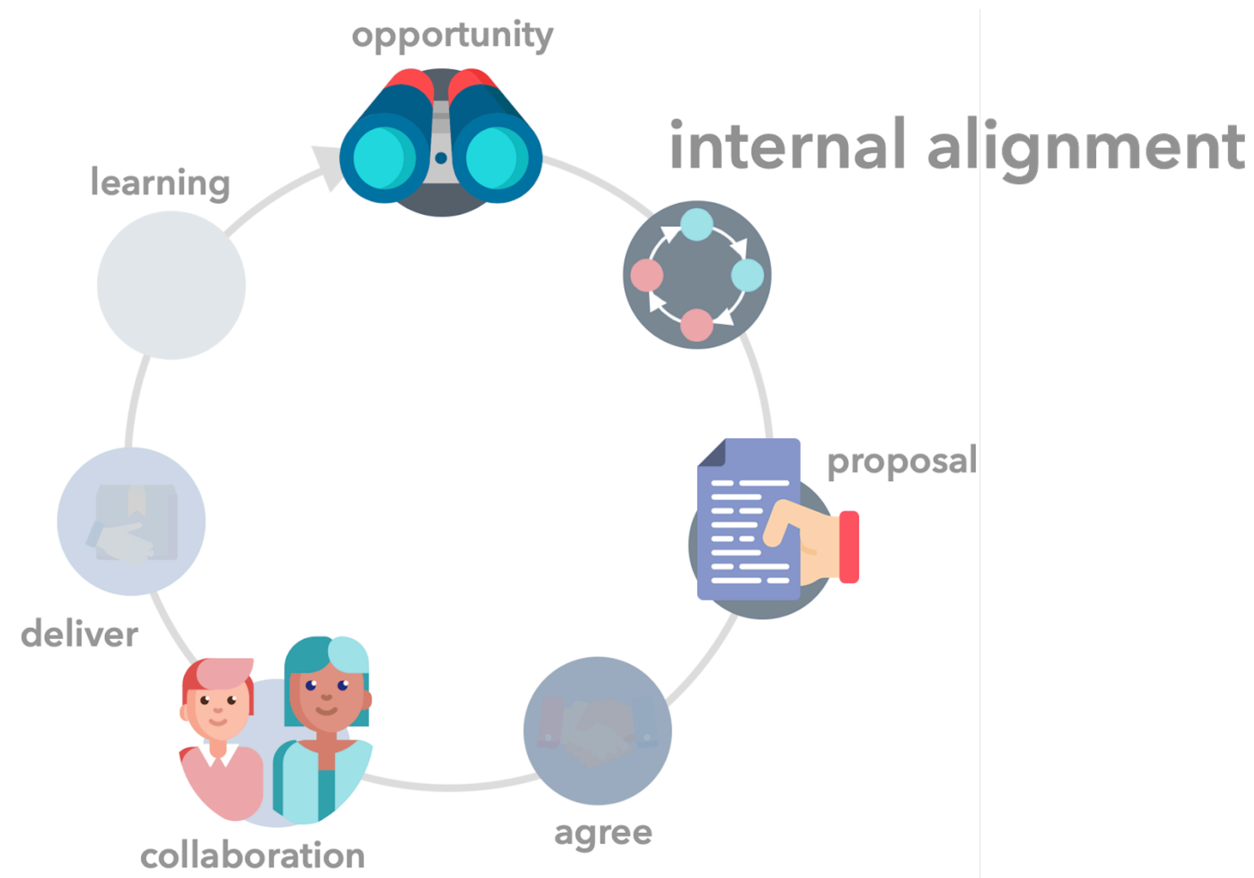


Figure 4.2 - Position of internal alignment step in framework

4.3 Framework

This subchapter proposed a collaborative data-design decision making framework. The framework in figure 4.3 presents an iterative process of synergising the data and design teams while aligning with the client's business value. This process aims to utilize both the data and design teams to use their strengths, find synergy between these in order to solve client's challenges. The process should be seen as both a way-of-working, but also a way-of-thinking.

4.3.1 Framework elements

The framework consists of two main spheres; an outer sphere resembles the context of the DCF, and the inner sphere the client's context. The outer sphere is built of six activities; the blue present the DCF's data science team, and the red the DCF's design team. For both teams, the activities, the required resources to perform these activities and resulting sub-deliverables are visualised. At the core of the inner sphere, the grey circle presents the client value. The framework supports the DCFs decision-makers by answering three crucial questions (1) what the client's perceived ROI of integrating data science and design for the specific challenge (2) what is the collaborative value that the data and design team to solve this client's challenge (3) does the project provide the resources to deliver that value is.

Two notions need to be drafted before the processes in the framework are discussed. First, the intention of the framework is not to grasp the complexity of interdisciplinary decision making (Newell, 2007). In contrast, it is intended to oversimplify so that the theory can be identified "in a socially recognisable form" (Orlikowski and Iacono 2001, p. 121). Second, although the framework presents a particular order of steps, it can be entered from any point.

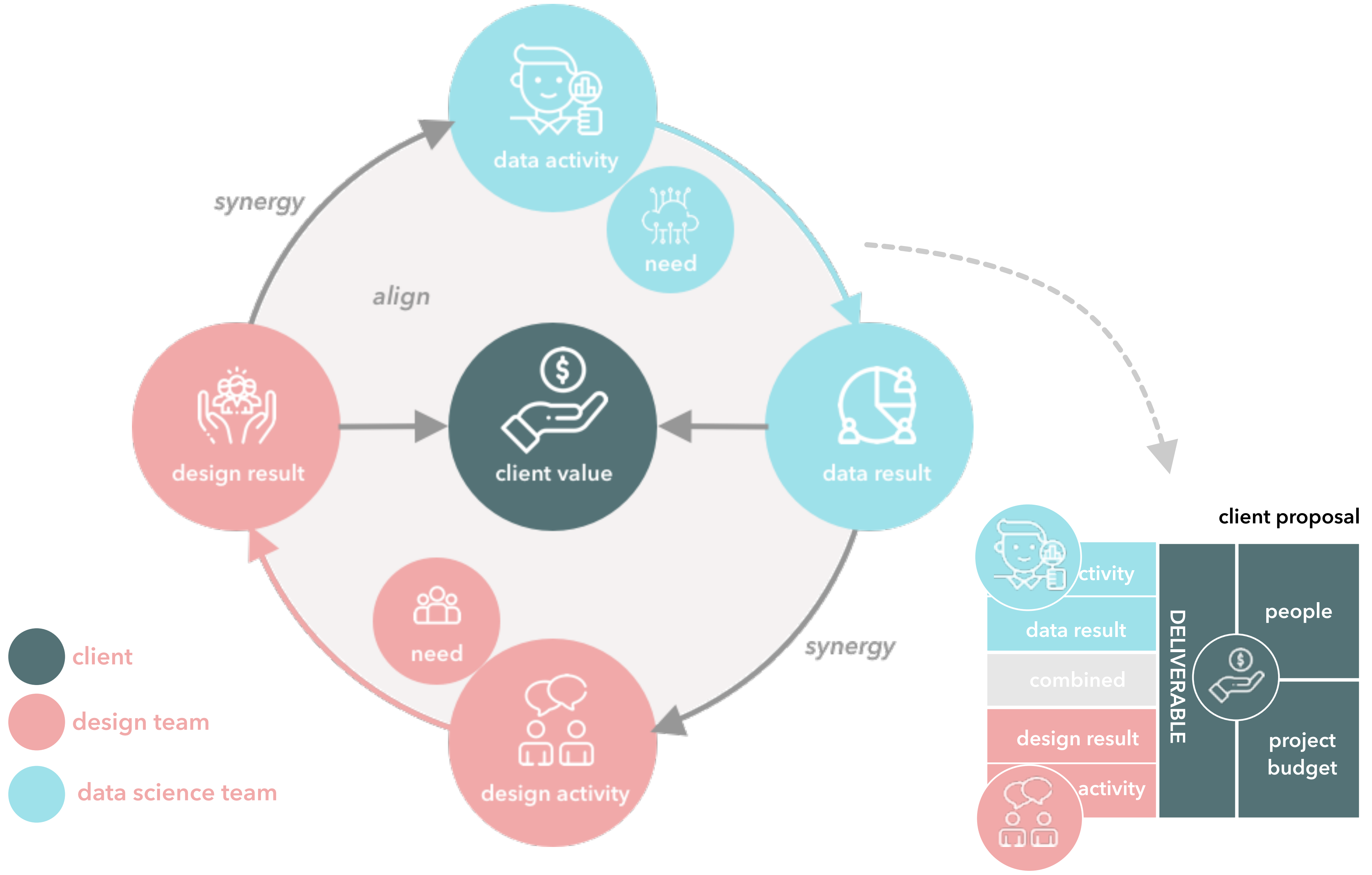


Figure 4.3 - Data-design collaborative decision making framework and relation to proposal format

4.2.3 Decision-making process

In figure 4.4, the process is proposed for interdisciplinary data-design decision making in the context of DCFs. This process is constructed based on the analysis of designers and data scientists using the framework during three collaborative decision meetings (see chapter 7.1.2) and is based on the two-part interdisciplinary decision-making process proposed by Newell (2007, p248). Newell argues that first, each discipline determines its perspective to a solution in a 'subsystem' before the two can be integrated. These 'subsystems' typify interdisciplinary decision-making complexity and can be viewed as separate decision-making routes that individuals take during the overall process (Newell, 2007). The proposed decision-making consists of four subsystems; understand, study, integrate and align. Appendix 4.1 provides an in-depth explanation of all individual steps.

4.2.4 Learning

In addition to decision-making, the meeting provides a place for learning and knowledge transfer (or "Ba", as Nonaka and Konno (1998) propose, a place to emerge and transfer tacit knowledge) between participants. The meeting allows both socialisation (direct from person to person by, for instance, observing) but also a safe environment for externalisation (make knowledge explicit by conversation) and internalisation (learn from these conversations).

Concluded from synthesising observations during the use of the framework and co-reflection after using the framework, three cognitive abilities should be aimed to be learned during the interdisciplinary decision-making processes. First, identifying linking sub deliverables is found to be both an influential decision and at the same time, a challenging one to make. An example of a linking sub deliverable is a service blueprint. Based on such a suggestion, designers know to develop a customer journey map, and data scientists know to develop a cost-benefit analysis of internal processes. However, to suggest such connections, the decision-maker requires a complex cognitive ability to view the client's challenge from both a data science and design innovation perspective, think comparatively between those and balancing internal feasibility with the client's desirability. Another issue found during interdisciplinary decision making is the difference in reasoning approach between designers and data scientists. The empirical research argues that both designers tend to be divergent thinkers while data scientists tend to be convergent thinkers (chapter 3.3.2) . These findings suggest that designers need to increase their convergent reasoning and understanding of the data science domain. Data scientists should learn to think more diverging and understand the domain of design.

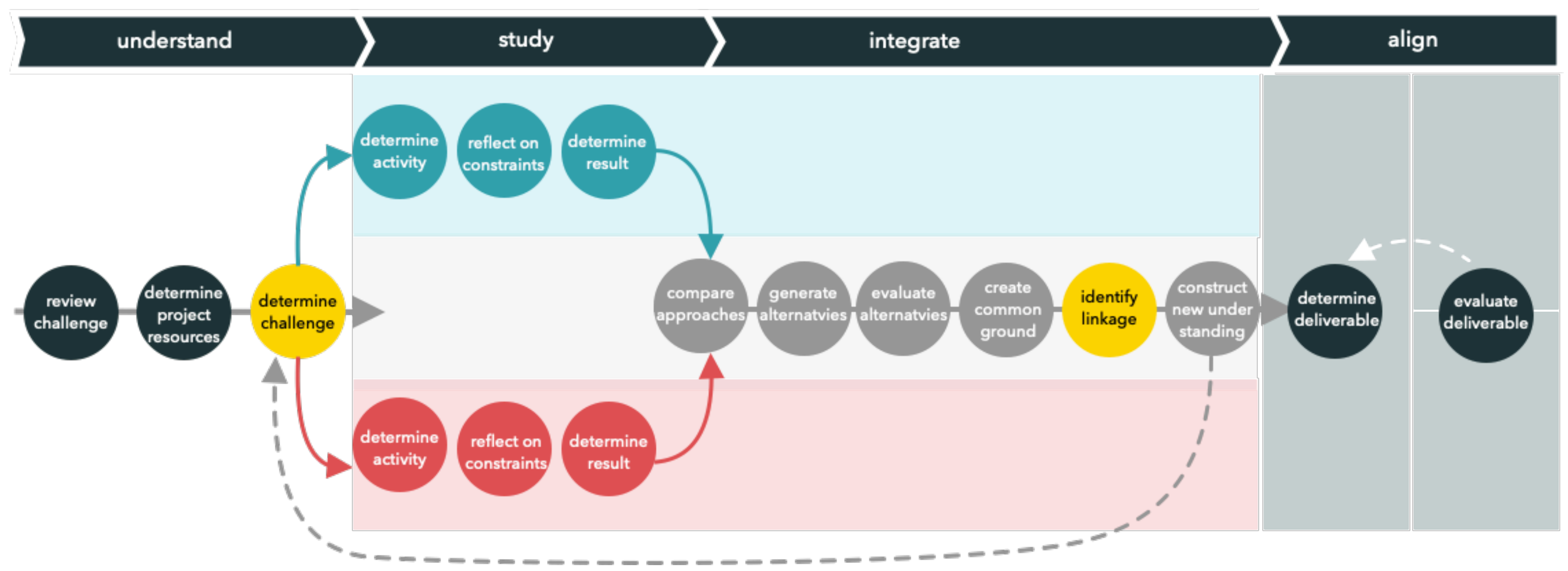


Figure 4.4 - Data-design decision making process - visualised on proposal framework

4.4 Design challenge

In order to facilitate the DCF with the integration of data science in design innovation, this chapter proposed the introduction of internal alignment during proposal drafting. This activity aims to support the target group, the DCF's data science- and design team's decision-makers, with interdisciplinary decision making. This activity aims to draft viable proposals to increase the amount of data-design collaborations, increase revenue, and decrease overhead costs. On the other hand, this activity provides a place for learning and improving to make better decisions and collaboration. At the core of this activity, a framework for data-design integration is introduced to structure the data-design decision-making process and supporting analyses.

To successfully implement this decision-making process, the DCF should emphasise changing the decision-maker's behaviour over time by a person-to-person knowledge transfer (see chapter 3.4). Concluded from analysing the interdisciplinary data-design decision-making process, such a person should have a cognitive ability: viewing the client's challenge from both a data science and design innovation perspective, think comparatively between those and balancing internal feasibility with the client's desirability. The DCF should provide a system where socialisation can occur between the data science- and design team's decision-makers and the person with this cognitive ability.

Enable the data-design integration by learning the DCF's data and design team's decision-makers to draft better data-design innovation client proposals. By facilitating a person-to-person knowledge transfer during the proposed internal alignment step, the aim is to improve the decision makers' abilities to interdisciplinary decision making.

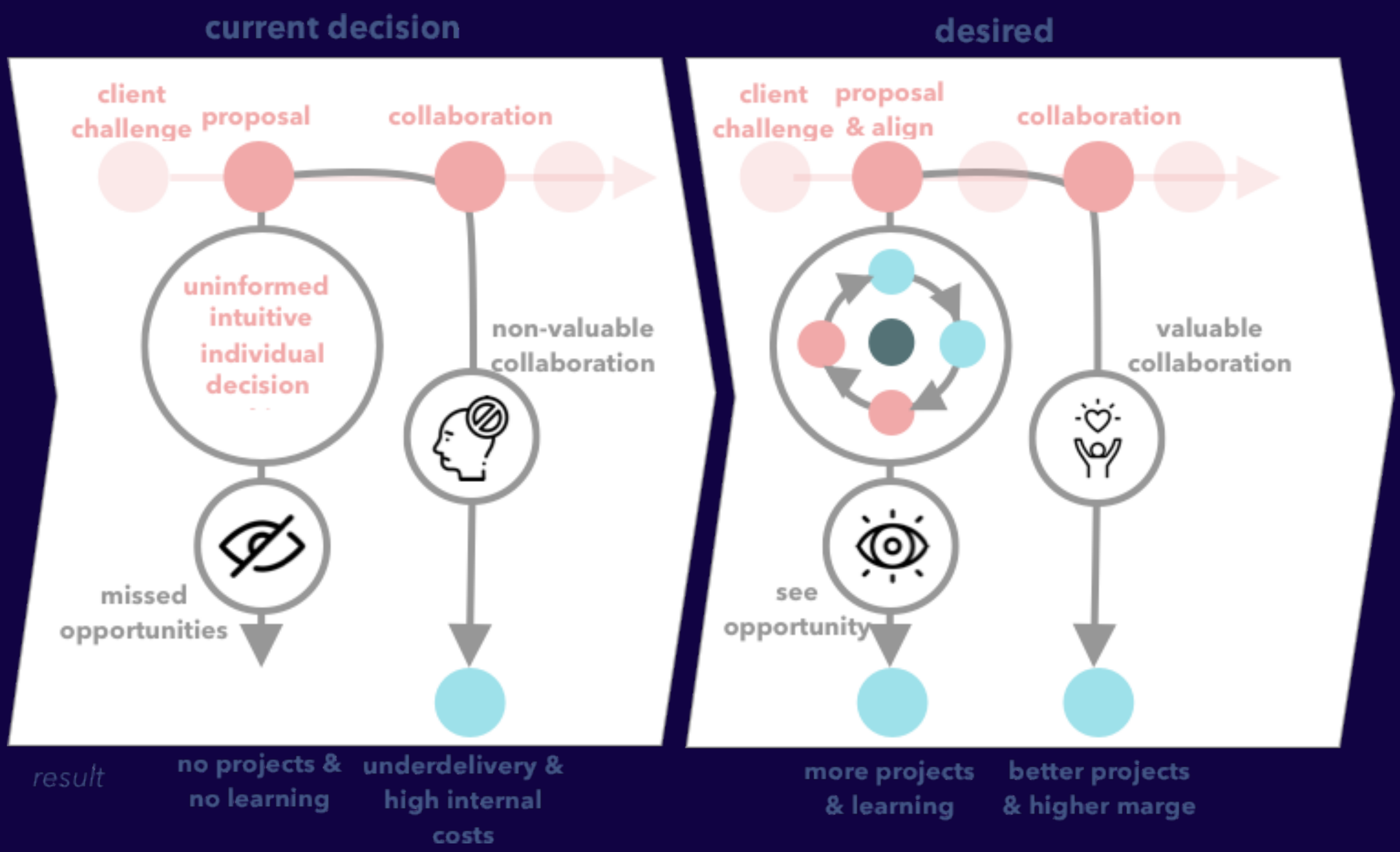


Figure 4.5 - Current decision making process versus desired situation.

Design requirements

Fit DCF
(1) support DCF's enterprise strategy
(2) fit in with DCF's pragmatic culture
(3) do not constrain DCF's agility

Fit organisation structure
(1) Fit with matrix organisation structure (Stanford, 2007)
(2) support the use of know-how between all teams (Stanford, 2007)
(3) support the development of new business opportunities (Stanford, 2007)
(4) break silo team structures

Data informed design
(1) support the opportunity of data-informed design innovation
(2) the fact that the data science process costs more effort and involves a go no go has to be taken into account during a data-informed design approach.

Fit teams
(1) The new solution should fit with both the data and design teams and team members
(2) integrating data science in the current multidisciplinary design-driven innovation approach.

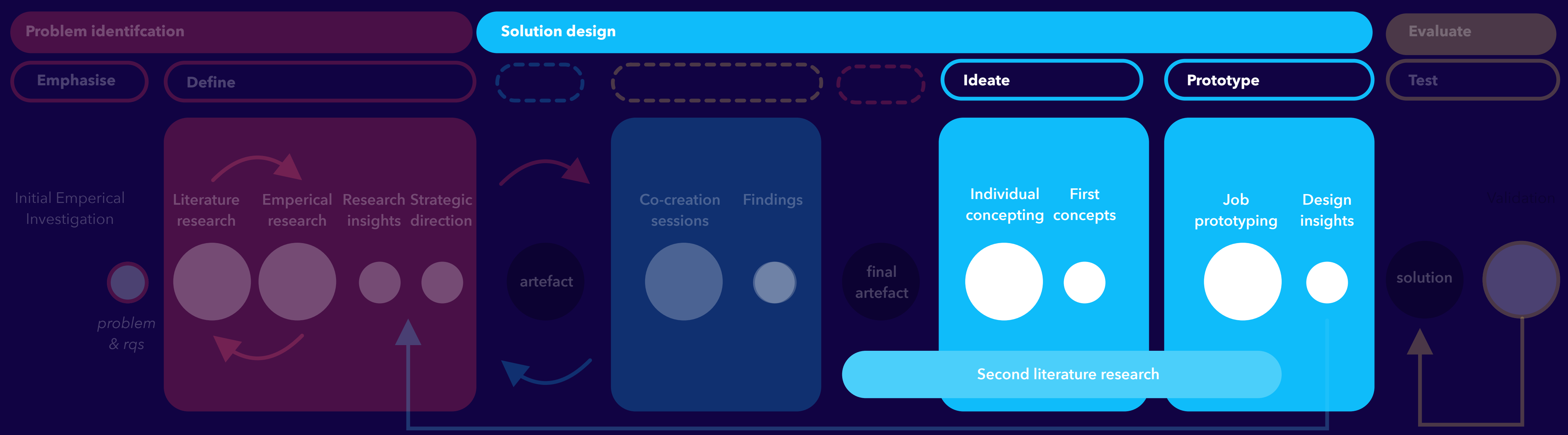
Learning framework
(1) the framework has to be learned to the decision makers by supporting the learning by providing steps that enable participating in thinking and doing.
(2) This has to be achieved by a person to person knowledge transfer.

Decision making
(1) The solution should aim to support the decision makers with high quality decision making by stimulating the enablers (knowledge present, elaborate with learning and iterate) and remove the constraints (language barriers, understand terms and critically reflect)
(2) collaborrative decision making
(3) Synergy between teams
(4) align with business value
(5) critically reflect on project constraints
(6) The solution should produce the decision makers to draft client proposals.
(7) accurate planning of resources
(8) predetermining the precise level of metric that is aimed to be combined with design insights.

5. Design process

This chapter discusses the activities performing during the ideation and prototyping phases of the research. The first chapter elaborates the design activities during an ideation and brainstorming session. Three concepts are designed. The second subchapter proposes job prototyping and role playing as an approach to iteratively design and evaluate intangible artefacts. The chapter concludes with findings from the job prototyping sessions.

5.1 Ideation
5.2 Job prototyping
5.3 Findings



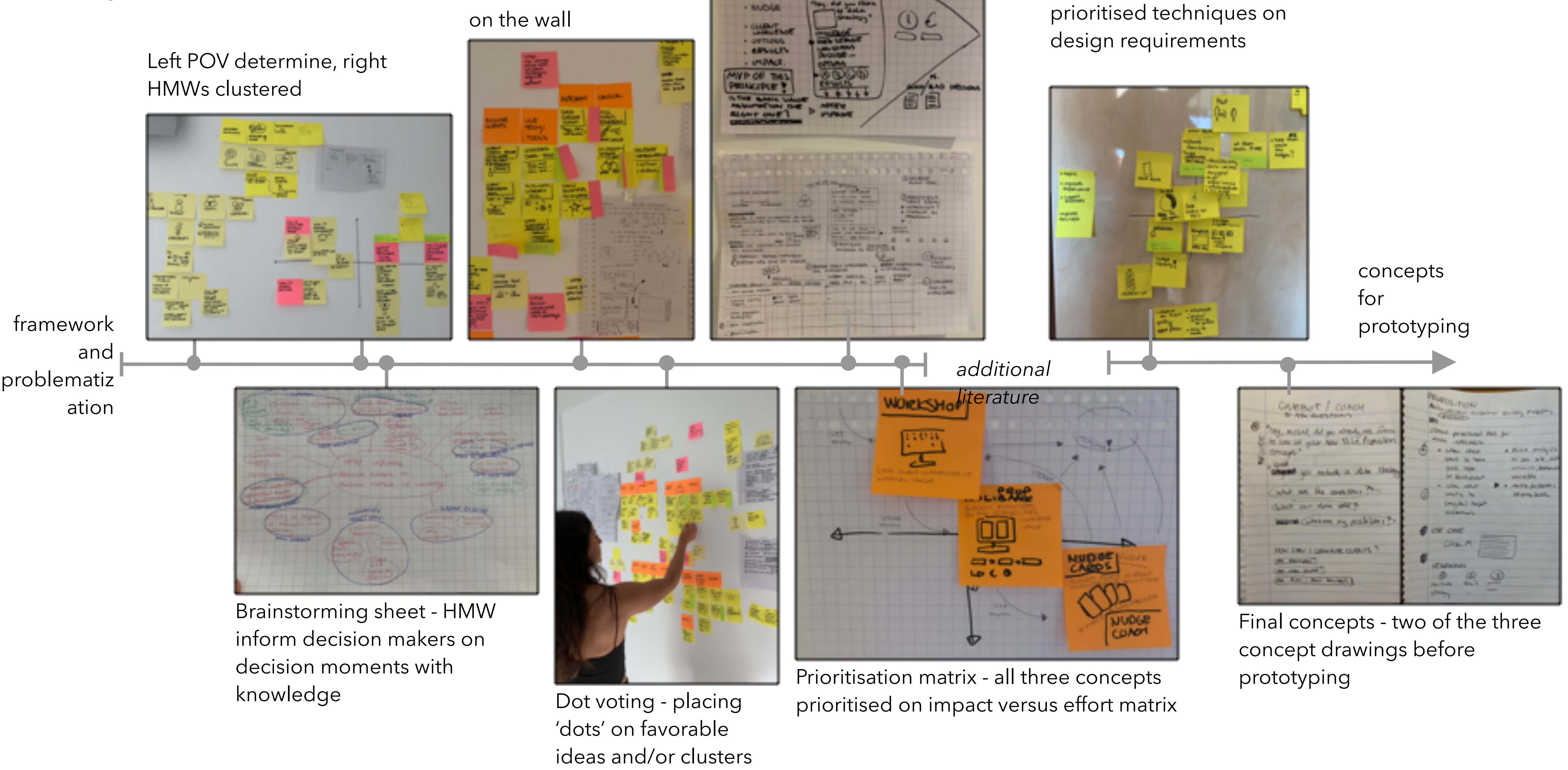
5.1 Ideation

This subchapter elaborates the design activities performed in the ideate step. The aim is to generate many ideas to solve the design challenge and prioritise these towards concepts. The individual concepting phase is performed by two activities; an ideation session and an individual concepting session.

Ideation session
An ideation session is performed to generate many ideas and develop the first concepts. Figure 5.1 provides images of the results of the steps in chronological order. Input for this session is the design challenge and design requirements drafted in chapter 4.4. The ideation session is 6 hours and is performed in 5 steps; frame challenge and determine point of view (2) brainstorm, cluster and prioritise HMWs (3) brainstorm, cluster and vote on ideas (4) combine ideas and concepting (5) prioritise concepts. An important technique used is brainstorming during this session. Brainstorming is a common approach for generating many ideas aiming to solve a design problem (Tassoul, 2006). According to Tassoul, brainstorming is driven by four rules of practice; postpone criticism, welcome 'freewheeling' (i.e. express any idea in a safe and secure environment), combination and improvements of ideas and quantity lead to quality (Tassoul, 1999). The ideation sessions resulted in the design and prioritisation of three concepts.

Concepting session
Based on the three concepts, additional literature research is performed. The 4-hour individual concepting session resulted in three concepts; a collaboration workshop between DCF's data science team and design team, a cross-team knowledge bank containing all data design innovation propositions and last 'nudge cards' able to support opportunity identification for possible data-design collaborations. These three concepts underpin the three prototypes (figure 5.3)

Figure 5.1 - Activities performed during individual concepting - chronologic order



5.2 Job prototyping

This subchapter elaborates on the activities performed during the prototyping phase. The prototyping phase is based on a newly proposed method - job prototyping. First, the need for job prototyping as a method is discussed from a strategic perspective and a research point of view. Second, the method of job prototyping is explained, and the literature that underpins this method. The chapter concludes with a visual representation of the prototypes.

5.2.1 Why job prototyping
Research suggests that a person is needed to transfer his or her knowledge regarding diagnosing data design innovation client challenges towards the DCFs data science and design team's decision-makers. Initial concept validations suggested that hiring new employees is a fruitful direction (see figure 5.3). However, hiring a person is found to be a threshold for management. Implementing prototyping (Liedtka, 2018) as practice for jobs could enable organisations to validate critical assumptions, learn critical aspects, and reduce the risk for management to hire new people.

The practice of designing jobs is referred to as job design. Job design refers to the actual structure, the tasks and activities employees perform for an organisation (Hackman and Oldman, 1980). Many scholars have strengthened the concept of job design. But all these directions focussed on either the strengthening of job characteristics, alternative outcomes or new moderating variables. None have explored the possibility to iteratively prototype job design. Prototyping is at the core of design thinking (e.g. Liedtka, 2015; Calabretta and Kleinsmann, 2017). Few scholars have explored the concept of job prototyping.

5.3.2 Job prototyping
This section proposes job prototyping and discusses the integration of this method in design science in information systems research (Hevner et al., 2004). Job prototyping can be viewed as an approach to rapidly prototype, test, and improve new jobs inside organisations before hiring a new job holder.

The method is based on the Job Characteristic model of Hackman and Oldham (1980), experience prototyping (Buchenau and Suri, 2000; Boess, Pasman and Mulder, 2010) and role-playing (Katja & Muellerone, 2012). Hackman and Oldman (1980) argue that managers can redesign jobs by designing work experience that provokes cognitive, emotional or behavioral reactions from employees. Buchenau and Suri (2000), view experience prototypes as "any kind of representation, in any medium, that is designed to understand, explore or communicate what it might be like to engage with the product, space or system we are designing".

However, prototyping concerning jobs raises questions about the possibility of developing artefacts, core for design science in information systems research (Hevner et al., 2004). Can intangible artefacts be developed and evaluated in the practical context? One literature study by Katja and Muellerone suggests that role-playing could reduce the risk of failures, allowing research contexts that cannot yet exist (Katja & Muellerone, 2012) to evaluate the change in the organisation in the context of information system research.

"Originated in theatre, this technique can be used to prototype complex socio-technical systems, in order to evoke certain experiences in users, designers, or developers, as well as to gather feedback about a certain concept for iteration purposes. "

- Katja & Muellerone (2012)

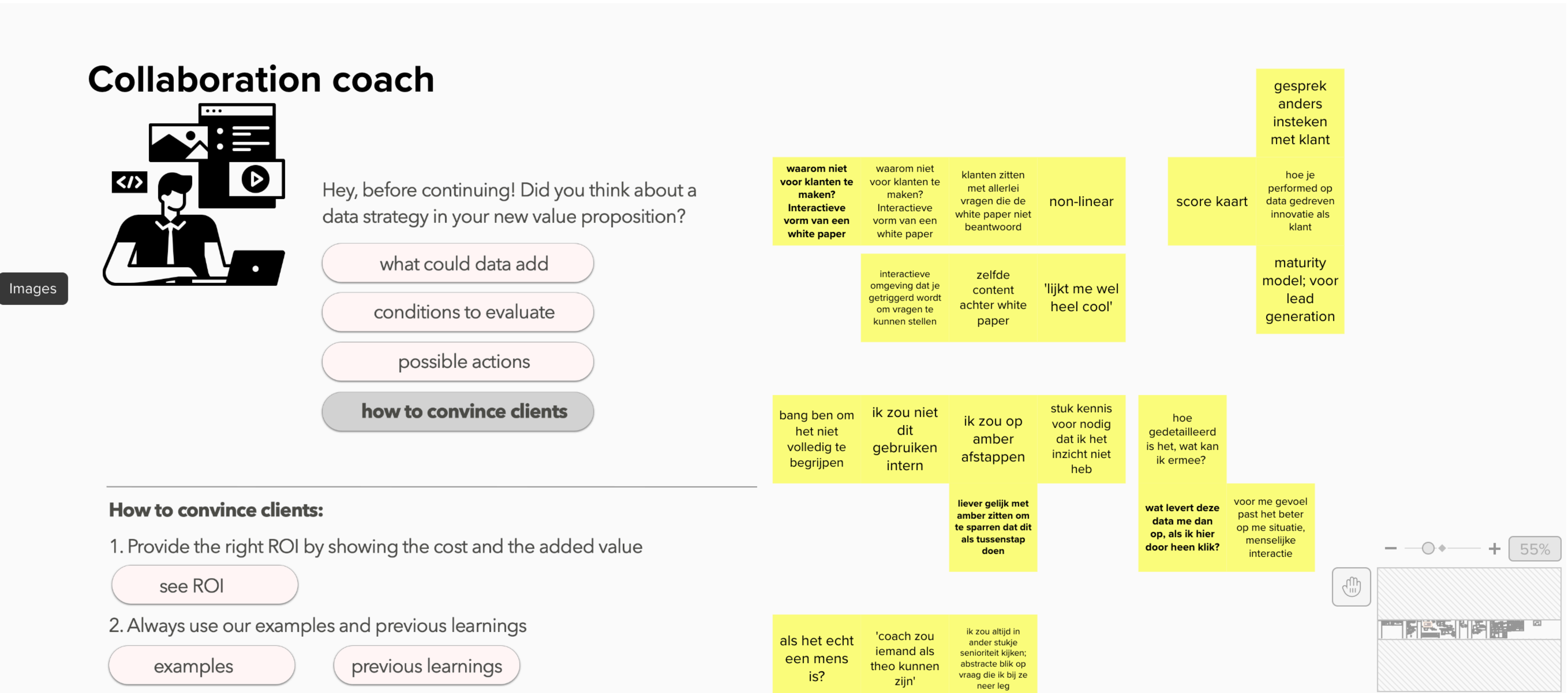
Role playing
In the case of job prototyping, this thesis argues using role-playing as a research method to test and evaluate possible changes to the information system. This process is based on the generated test cycles of (Simon, 1996). The purpose of role-playing in these cycles is to gather feedback. This means that that new knowledge generates new knowledge based on externalising the participants' experience (tacit to explicit knowledge). However, the disadvantage is the validity of the findings, to reproduce the experience and find the same findings. For this reason, triangulation is used to increase validity of the findings; observations from the author, notes from the externalisation experience during, and last a reflection on the experience itself afterwards.

In order to support the job to be evaluated in a practical context (the job in itself is an intangible artefact; knowledge, skills, tasks, activities in itself cannot be designed), design tools are used. Personas can be created to present the jobs profile, including the knowledge and skills needed. Storyboard or written scenarios provide visuals or textual representation of a story about the tasks and activities the job-holder performs in the organisation's context. (Boeijen et al., 2013).

5.3.3 Procedure
Five job prototyping sessions are performed. The participants were purposefully selected as decision-makers. Participants from various seniority and team positions are selected to form a holistic view, including; three designers (including the proposition lead), the data science and strategy lead, and one strategy consulting. The sessions are performed online and range from half an hour to an hour. The session is audio recorded, and notes are written down.

The sessions are divided into three sections; an introduction, role-playing and a co-reflection. During the introduction, a storyboard is presented and discussed with the participants. During the scenario, role-playing, the prototype (see figure 5.3 for the prototypes) is presented without the observer's interference. The participants are asked to think out loud and elaborate on possible interactions. During this step, the observer does not interact to decrease influence and feedback is written down. During the co-reflection, notes are written down, and the previous statements are presented back to the participant. This is especially important to guarantee the validity of the findings (Golafshani, 2003).

Figure 5.2 - Early validation activity - post-its on Mural



'only after a month I knew we I and the designer were actually collaborating on the same project'.
- designer during prototyping

5.2 Findings

The 'data-design coach' is perceived as highly valuable by participants. Initial concept validations suggested that hiring new employees is a fruitful direction. Therefore, the new role is further developed during job prototyping. Based on the analysis, three important additions are found that directed the final design solution.

This new data-design coach is suggested as the one that should facilitate the alignment meeting and transfer his knowledge to the data and design decision-makers. During prototyping sessions an interest event accured, the DCF's strategy team and in specific one strategist is recognised as highly suitable as a potential job holder. Prototyping with a potential job-holder provided valuable insight in the necessary profile and the leadership styles that can facilitate data science integration.

The current leadership style of strategist during collaboration is identified as a directive one. A data scientist elaborates, 'only after a month I knew we I and the designer were actually collaborating on the same project'. Based on prototyping, to transfer knowledge, the leadership style should change towards a facilitating one.

In addition to the alignment meeting, two activities are argued by the participants to support this role. First, the job-holder should use rational overrides (van Lieren, Gallabretta & Schoormans, 2018) to support the opportunity identification of the data and design team's decision-makers. Without this activity, many opportunities still will be missed. One of the participants referes to these overrides as, "these kinds of actions are actually how it should be done". The participants argued that these rational override should (1) inform the decision-maker on the opportunity, (2) provide the argumentation of that opportunity and (3) refer to the 'knowledge holder. The second additional activity is performing projects. The strategy lead, argued that 'such a senior profile will only be hired if he would participate during the project.

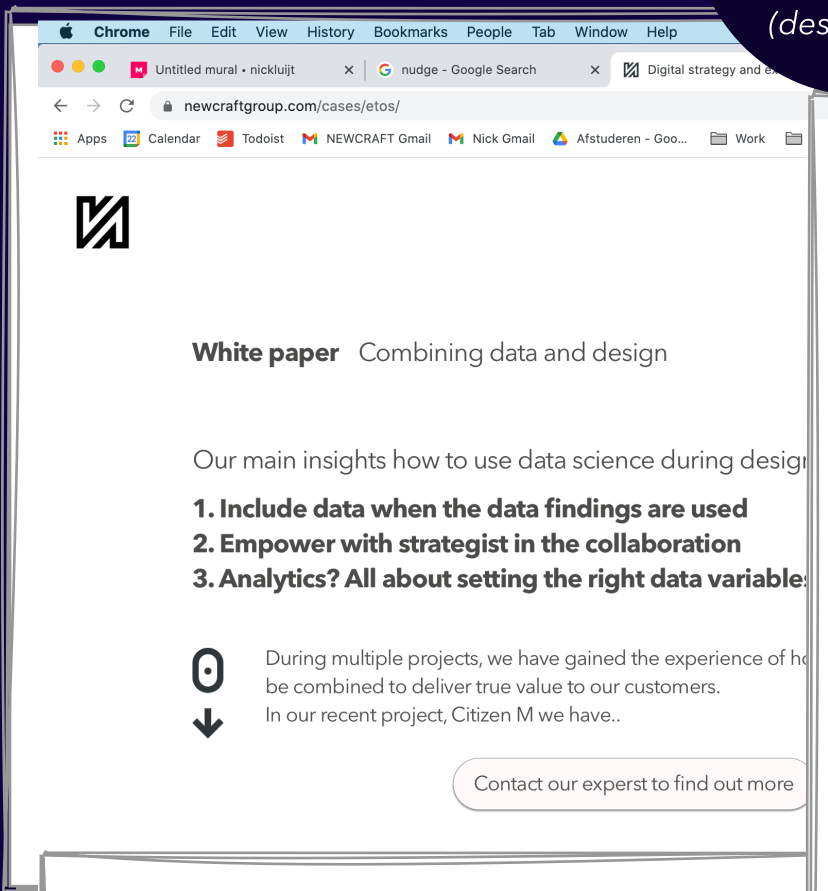
Additional design requirements
Job-holder
(1) The position thus should be more facilitating than directing to enable integration between the two teams.
(2) The job-holder should be at the intersection between data science, design and business.

Nudging
(1) The solution should aim to influence the DCFs decision-makers' behaviour by using rational overrides, ie. create a moment of friction to reflect on possibilities (van Lieren, Calabretta & Schoormans, 2018) at decision moments.
(2) This intervention should inform the decision maker on the possibilities of collaboration; combining data in design
(3) Refer to a colleague (interpersonal networks) who can provide deeper understanding (knowledge) on the specific subject of the decision to be made.

Decision making
(1) The decision making should be effective and efficient.
(2) The possibility should be quickly assessed if potential collaboration is possible
(3) Use previous learnings for an accumulation of knowledge (Cronholm, Gobel & Rittgen, 2017)

1st prototypes

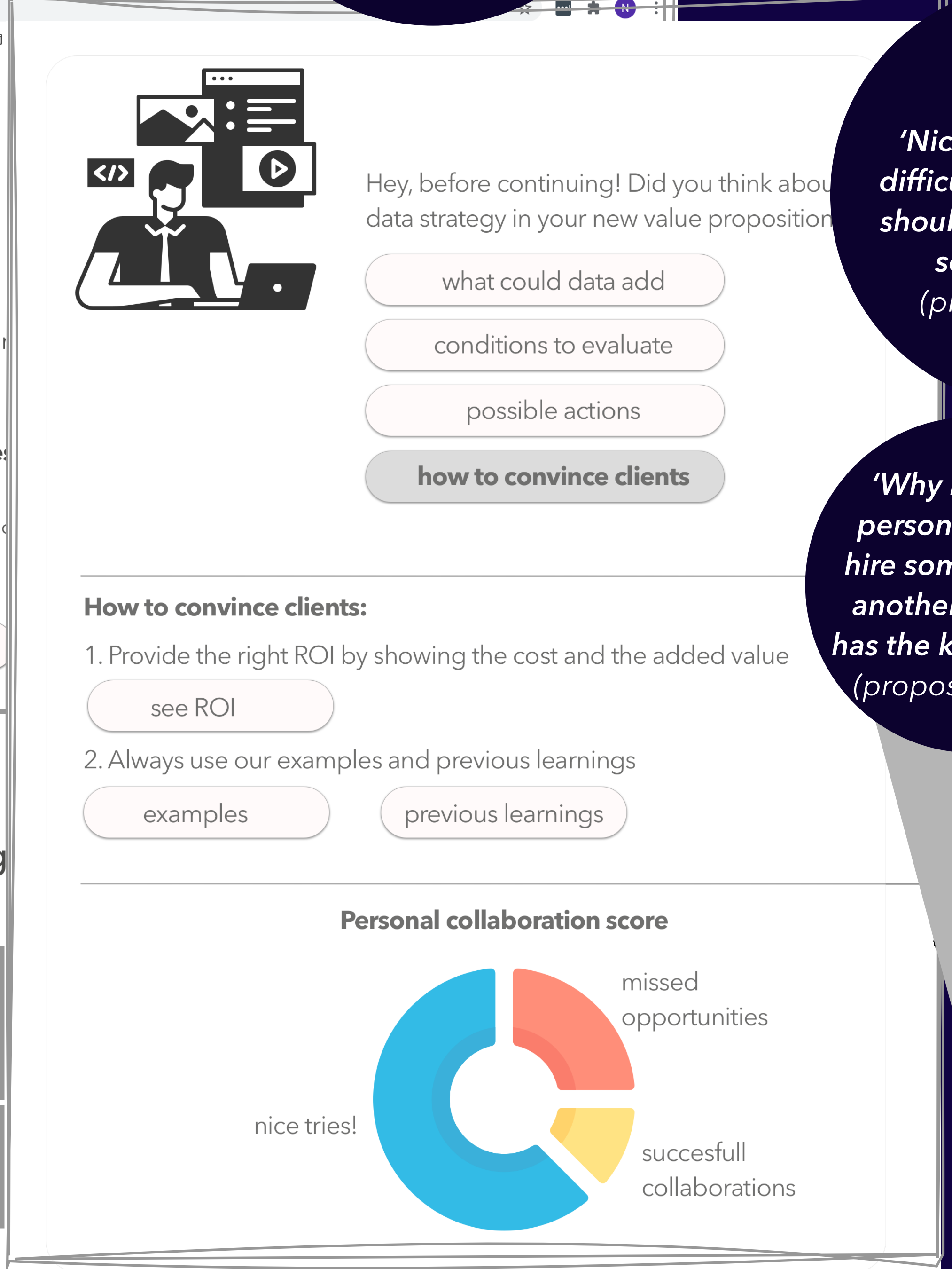
white paper - sharing of DCF's best practises on website



'Communication to clients can really start a valuable discussion'
(design lead)

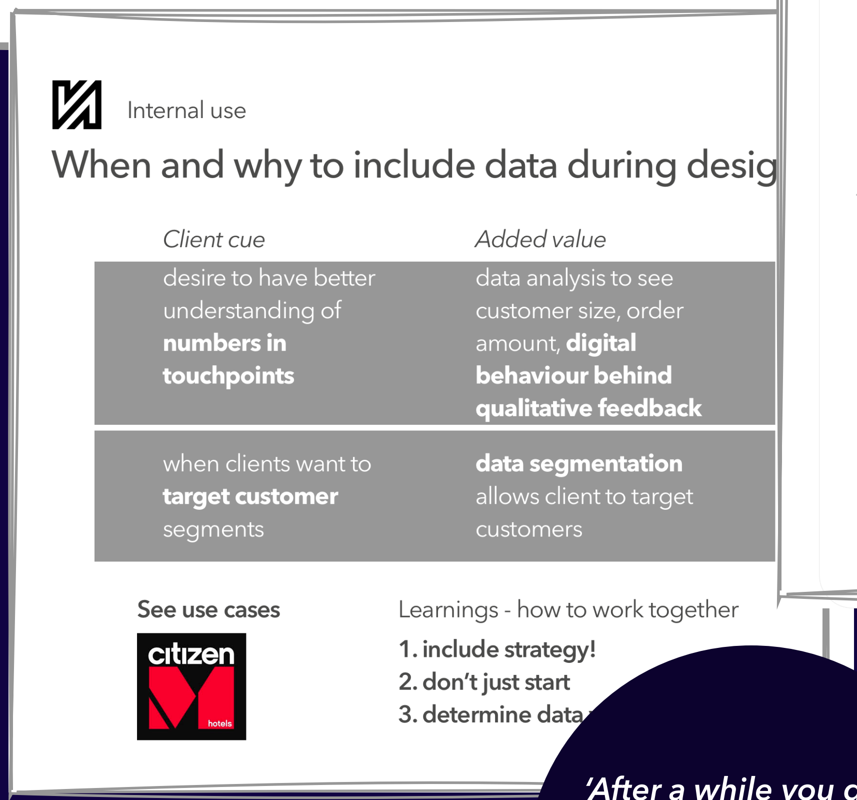
'I would rather speak to them with a presentation, that gives more energy'
(designer)

(virtual) data design coach - online coach that supports employees in acquiring data design innovation projects



'Nice! I always find it difficult to know when I should involve the data scientist or not'
(proposition lead)

'Why not a real person? Why not hire someone from another firms that has the knowledge?'
(proposition lead)



'After a while you don't look at it anymore, you don't know to look at it'
(service designer)

Internal knowledge bank consisting of data design innovation opportunities, the client's added value and learnings from previous cases.

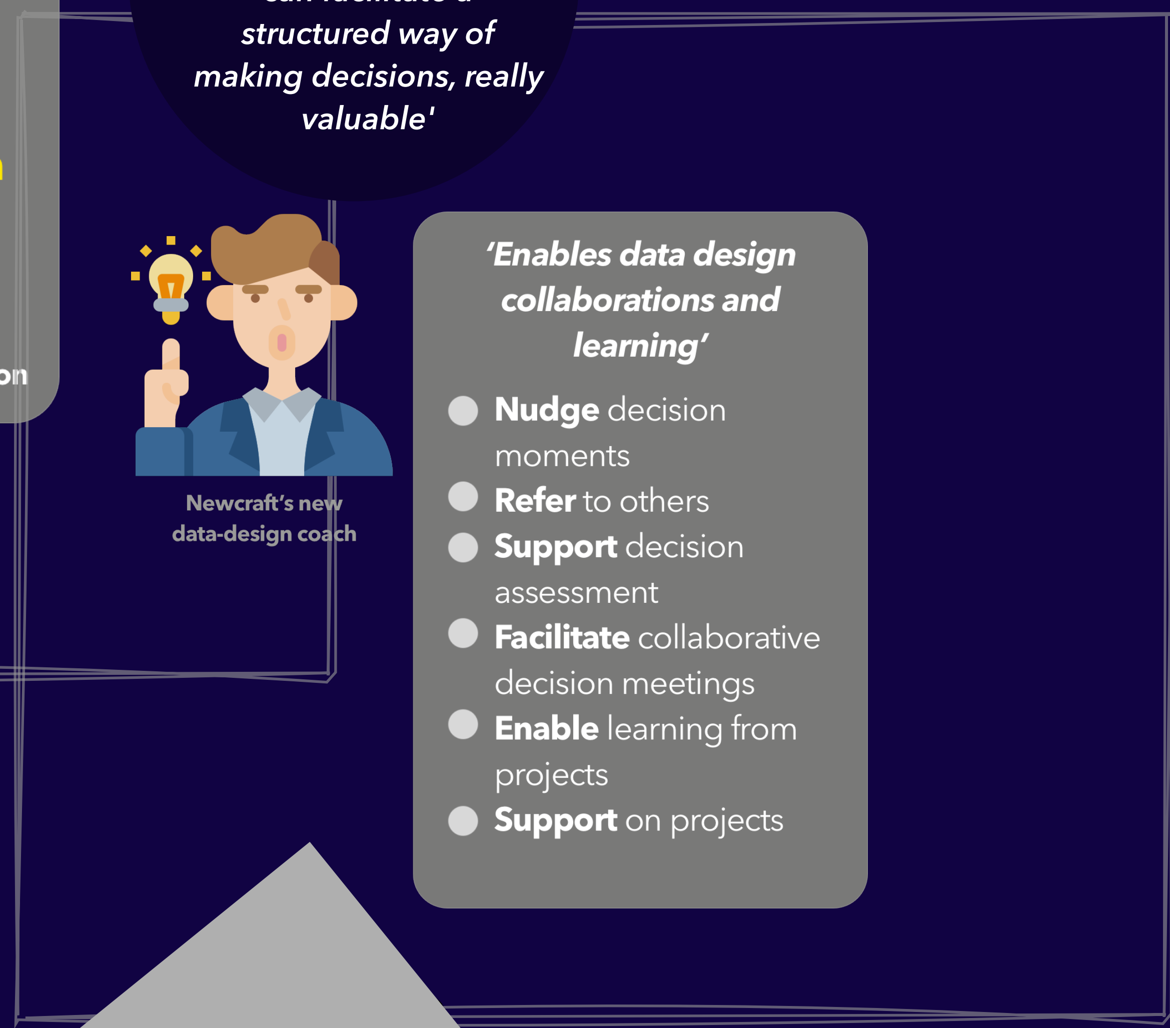
'I really belive in this and would be really valuable, but is an enourmus job'
(proposition lead)

2nd prototypes

'This is how it should be'

'Although I think that all senior people should have this'

'Because there are so many factors that influence these decisions, if this 'thing' can facilitate a structured way of making decisions, really valuable'



Data design coach - new role that support the identification of new opportunities, and directs them to another employee

Data design coach and activities - set of activities, from nudging to enabling learning

Last prototypes

The coach should frame the challenge already from his perspective, otherwise I don't understand why he is hired?'
(designer)

*'The idea of having a meeting a f*cking amazing! Determining if a project fullfills a data design project'*
(designer)

'I dont believe in using examples, I believe in quarterly meetings and sharing all the results, you want to know it before you start'
(designer)

'I want a little more argumentation of the opportunity'
(strategy lead)

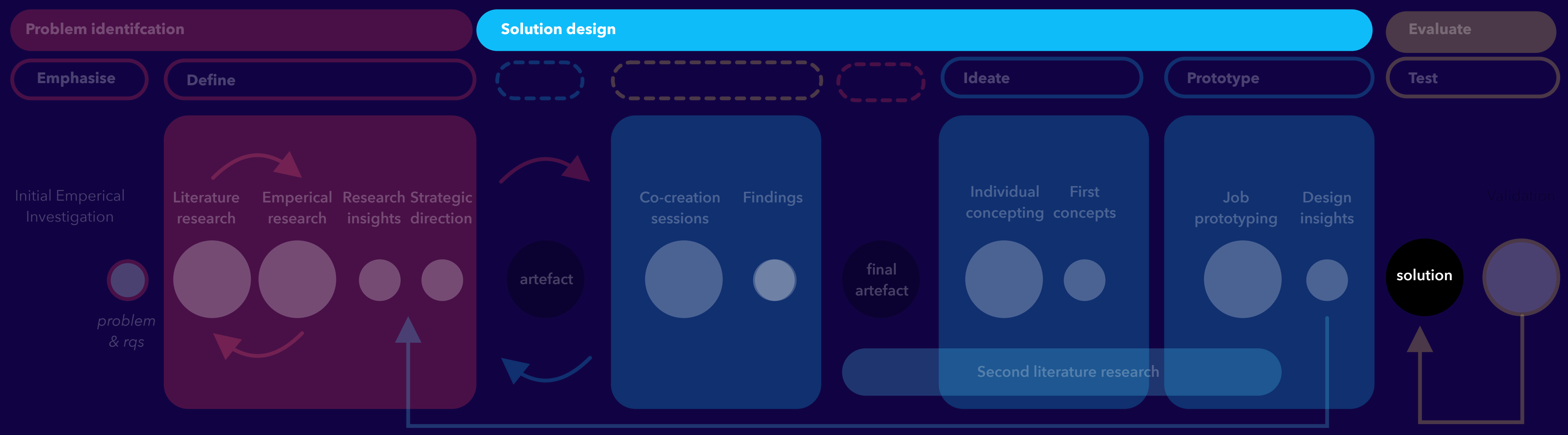
'Using the examples of previous projects at this point would be really valuable for inspiration'
(service designer)

Data design coach and toolkit - the coach support opportunity identification, a quick decision meeting and facilitates collaborative decision making.

'The art of this person should be to bring both blood groups together'
(strategy lead)

6. The data-design lead

This chapter proposes the implementing a new role, the data-design lead. The first subchapter discusses the lead's facilitating role, three activities and needed profile. The second subchapter discusses the recommendation to the DCF regarding the implementation of this role in the organisation.



The data-design lead, a hinge between the two teams

Figure 6.1 - The data-design lead, a hinge between the two teams

The solution argued is the introduction of a new role; the data-design hinge. This data-design lead is a pivotal role in the collaboration and integration of the data and design teams, functioning as an 'organisational hinge' between the two teams. The implementation of the new role is clarified with the use of a hinge as a metaphor. As the integration of the data and design team cannot be done by the teams themselves, a hinge must be implemented to connect them. Someone that is able to connect the 'design wall' and the 'data door'. Something that is strong and yet flexible. And while the door and the wall are the main components that support the function, they just need one pivotal piece to operate the door. A door and a wall without a hinge could function (picking up the door is possible) but a hinge between them provides so much more value. In this section, the new role is discussed by the new job-holders role, responsibilities, activities, profile and position.

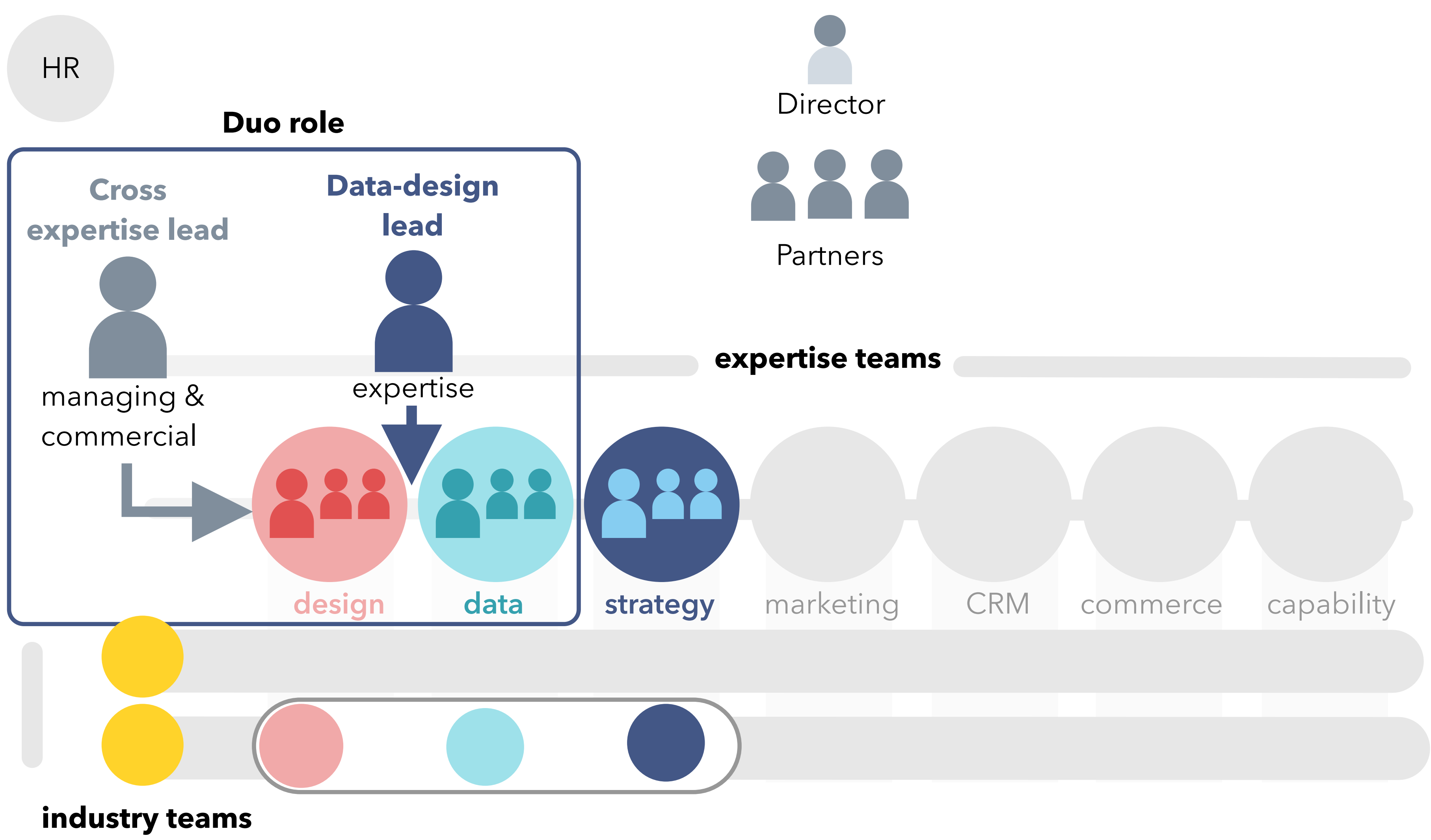


Figure 6.2 - Duo role mechanism inside orgnisation structure DCF

6.1.1 Role in organisation

The data-design lead is responsible for managing the integration of the DCF's data science and design teams. The lead is part of a duo-role mechanism, consisting of one general cross-functional (or cross-discipline) manager and one specific data-design manager (see figure 6.2). The cross-functional lead has general responsibilities for the commercial and managerial tasks concerning all cross-functional integrations. In contrast, the data-design lead not responsible for any managerial task but the management and facilitation of data-design expertise knowledge. In contrast to current team-leads (who are required to both do the managerial and expertise), the two roles ensure integration from both a managerial, commercial and discipline level. The main argument for the divide is the impracticality of finding such a skilled person that both has working experience in data science, design, business strategy and managerial capabilities. The profile will be explored more in-depth in chapter 6.1.3.

The data-design lead's central role is acting as a sparring partner to the DCF's data scientists and designers based on his expertise regarding data-design integration. At the core of this role is the data-design decision framework (see chapter 5). If the data-design lead can be compared to a hinge, the framework can be perceived as the joint. The lead aims to transfer his way of thinking regarding the diagnoses of data-design integrations towards the data and design team's decision-makers by facilitating the frameworks' way of working. This leads to positive behaviour change regarding collaborative decision-making, which enables more collaborations to occur. These actual data-design collaborations will be the most crucial source for further integrating the data and design teams, changing the DCFs data design innovation approach from a multidisciplinary approach towards an interdisciplinary approach.

Leadership style

To enable the data-design integration maturity to grow, the leadership style of the data-design lead needs to change as well. To better understand the lead's leadership styles, the Situational Leadership model of Hersey and Blanchard (1969) is used. Hersey and Blanchard argue four types of leadership depending on (1) the amount of directive behaviour and (2) the amount of supportive behaviour. Proposed are three types of data-design leadership styles; directive, facilitating and project-based. In figure 6.3, these three styles of leadership are visualised in three phases. The three leadership styles are highly determined for the aimed maturity of data-design integration; a directive style for multidisciplinary, a supporting style for interdisciplinary collaboration, and a project-based leadership style for transdisciplinary.

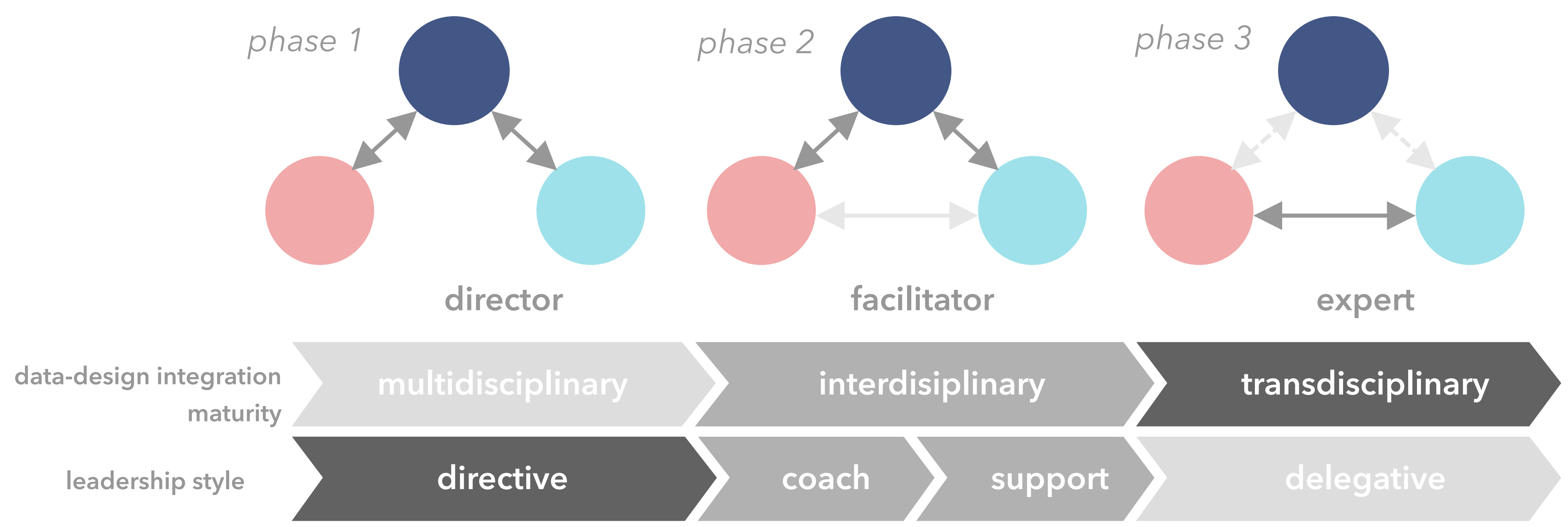


Figure 6.3- Three positions of lead over time - increase maturity and decrease directive style

6.1.2 Activities and tasks

The data-design lead performs three activities; supporting data-design opportunity identification and performing data-design projects (see figure 6.4). As mentioned, the core activity is the data-design decision framework proposed in chapter 5. If the data-design lead can be compared to a hinge, the way-of-thinking visualised in this process can be seen as the joint. The lead aims to transfer that way-of-thinking (cognitive ability) to the decision makers, by facilitating the way-of-working (process). This in the end is going to ensure the integration of the data and design team.

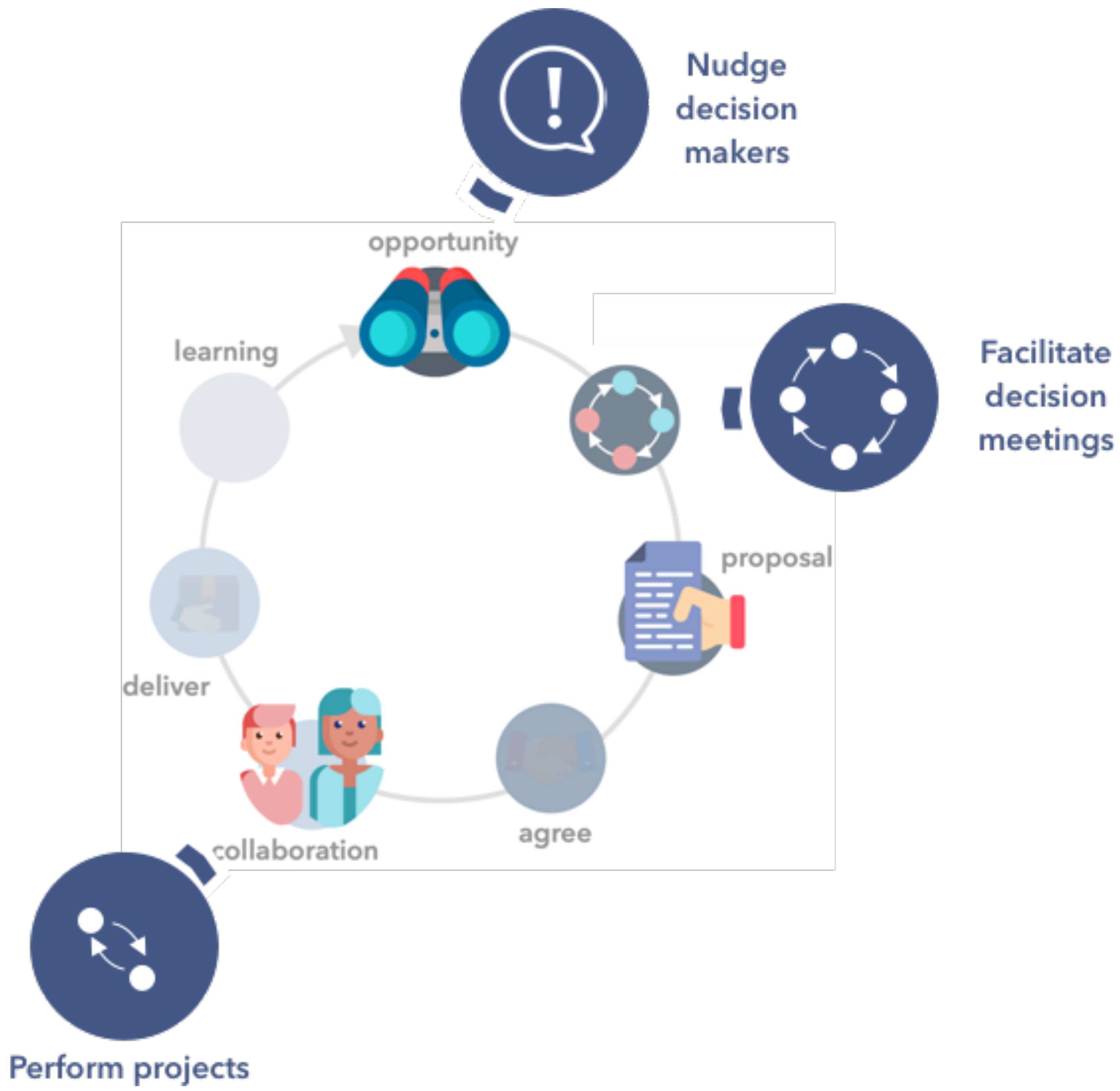


Figure 6.4 - Three activities performed by lead - nudging, facilitating & performing project

Facilitate decision making during the proposal

The goal of this activity is to draft practical data-design project approaches by structuring the internal data-design process. This way of thinking ensures the DCF's data and design team understands each other's activities, maintains synergy, and continuously delivers relevant client value. The activity is facilitated by the data-design lead and is performed between DCF's growth leads, project lead and relevant expertise. The activity takes place in a meeting ranging from one to several hours, depending on the decision's difficulty.

Central to this meeting is the collaborative data-design decision process visualised in figure 6.5. This process aims to utilise both the data and design teams to use their strengths, find synergy between these in order to solve client's challenges. This way of thinking is the xxprimary ability that needs to be learned by the data and design decision-makers and currently is only tacit knowledge (i.e. in the head of) the data-design lead. The lead aims to learn this way of thinking from the decision-makers by supporting and coaching the collaborative decision-making process. During these meetings, the data design lead needs to perform five actions to support the collaborative decision process.

Align teams - During the meetings, both teams tend to misalign in culture. This makes communication and collaborative decision making difficult. The task of the lead is to get the data and design teams on the same wavelength by communicating and translating both discipline 'languages'. The lead can do this by clarifying terms himself, but more advice is to nudge the participants to explain these terms themselves.
Discussion starter - During the generation and evaluation of alternatives, the strategist coaches and supports the decision-makers. Providing suggestions for alternatives, being asked or actively coaching decisions, and ability to challenge current thinking.
Clarifying alternatives - During generation and mostly during evaluation, the lead needs to make alternatives clearer to the decision-makers. Three tools can be used to perform this activity: (fictive) issue trees, examples of previous projects, and analogies. The ability to quickly draft issue trees aims to enhance the clarity, thoroughness and coherence of the analysis (Chevallier, 2016).
Choose - At some instances, especially when the maturity of the present data and design teams' decision-makers is low or the time pressure is high, the lead needs to take decisions. The purpose of these decisions is to unite the teams and steer them in the right direction. These decisions primarily concern collaborative deliverables that guide both teams to determine their activities to support and reach that deliverable. It is essential that during these decisions, the lead needs to communicate this choice with convincing and clear argumentation from working experience.
Business central - During many instances, the lead needs to challenge the participants on aligning activities with the client's business goals. The focus should be put on calculating realistic FTEs and a feasibility budget. Designers can be challenged to calculate the client's economic value rather than user values. Data scientists can directly dive into technical complexities and be challenged by asking the data scientist to draft data solution alternatives on an impact versus effort matrix.

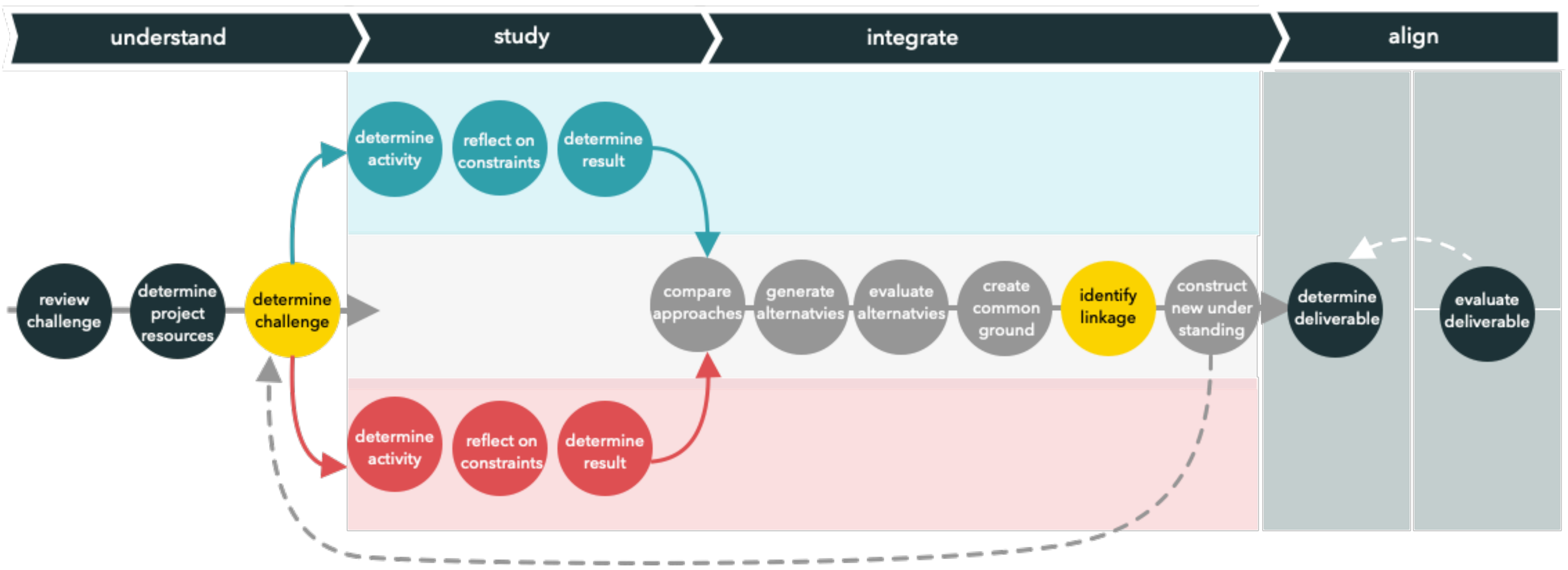


Figure 6.5 - Data-design decision making process - visualised on proposal framework

Activity 2 - Nudging

A secondary activity is supporting the decision makers with the identification of data-design project opportunities (see figure 6.5). Many decision makers currently make intuitive and uninformed decisions that cause the missing of opportunities. Without performing these activities, the collaborative decision process (activity before) would not be done as many times as it could be, as the decision makers currently miss a lot of opportunities. To counter this intuitive behaviour and allow decision makers to consciously think about opportunities, the lead uses rational overrides. ‘A rational override is a small moment of intentional friction that attempts to influence people’s behaviour or decision-making by intervening automatic thinking and activating reflective conscious thinking (van Lieren, Gallabretta & Schoormans, 2018).

Two approaches are drafted to perform this activity; actively coaching and passive supporting. The two approaches differ in the amount of effort the data-design lead. The activity gradually changes to a more passive role as the maturity of the decision makers grows in identifying these opportunities themselves. First, actively coaching alerts the decision maker to make the decision makers aware and to persuade them to perform desired behaviour (Jung and Mellers, 2016). After this alert, the decision maker can provide real-time feedback, to show the consequences of the actions and encourage them to adjust and improve current behaviour (hansen and Jasper, 2013). Second, passive coaching can be done by sharing information beforehand. Beforehand we create commitment from the decision makers. These commitments should be detailed and action oriented (Hansen & Jespersen, 2013). The aim of this commitment should be to design an override for people themselves during the decision moment in which they need to see the possibility of asking the data design coach as an 'extra decision point'. During the decision moments the decision makers can go towards the coach as extra decision points (Cox & Gould, 2016) and provide real-time feedback (Hansen & Jespersen, 2013). After the projects, the coach can evaluate the actions made and show performance relative to others (Hansen & Jespersen, 2013) and provide personalised feedback (Frsysak, 2016).

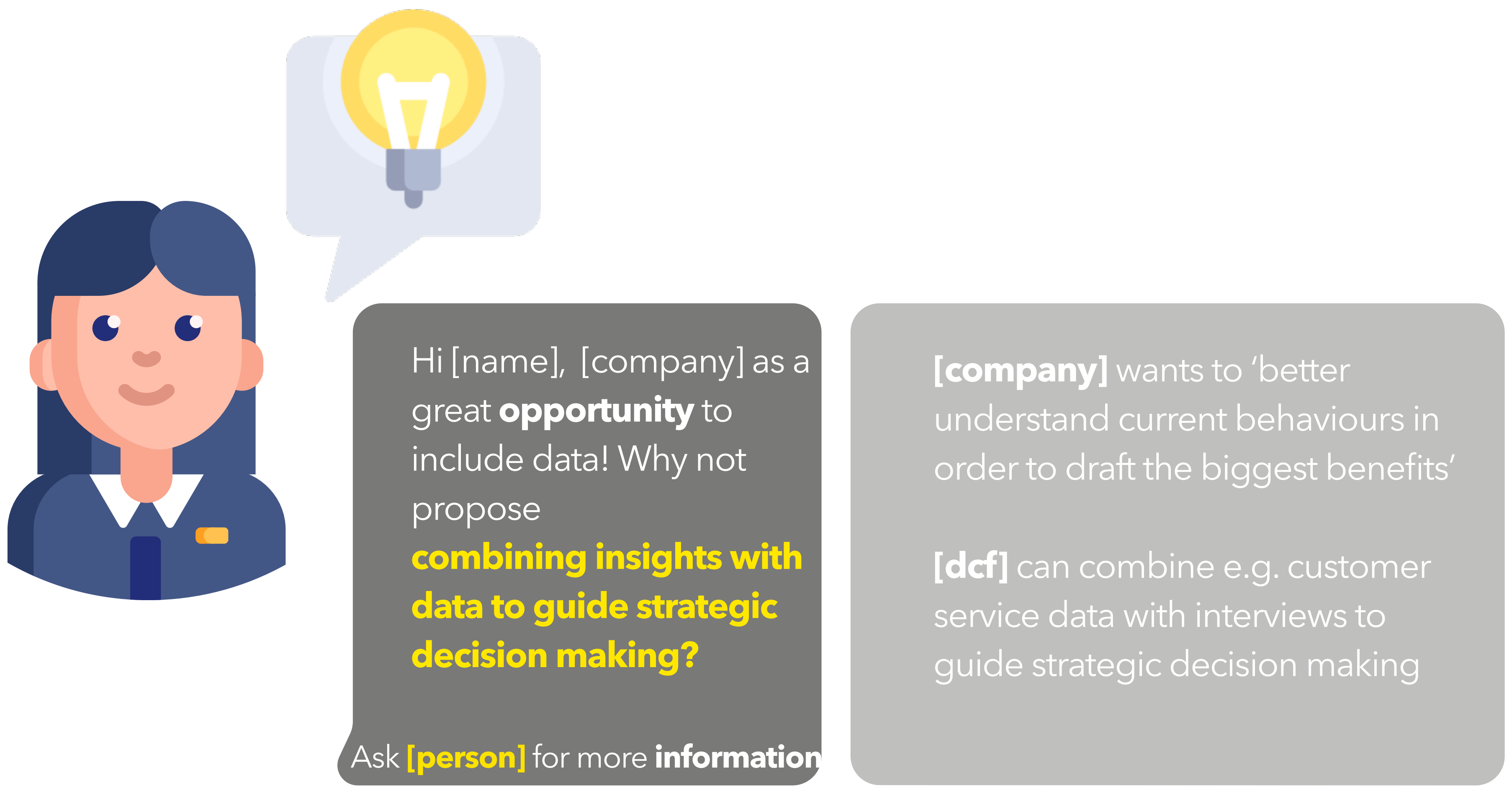


Figure 6.5 - Nudge of the coach: opportunity, explanation and referring to collegue

Activity 3 - Perform projects

The last activity the data-design lead performs is peforming data-informed design innovation projects. During these project the lead performs both standard strategy activities as visualised in figure 6.6; business case development, market research and business case delivery, and supportive activities; hypothesis development, sharing business insights and translation of data insights. Especially the first activity is crucial to secure aligning of the two team’s results. Without prior drafting the expected hypothesises, the data team would either be to late with the data understanding or have data that do not suit the design team’s results.

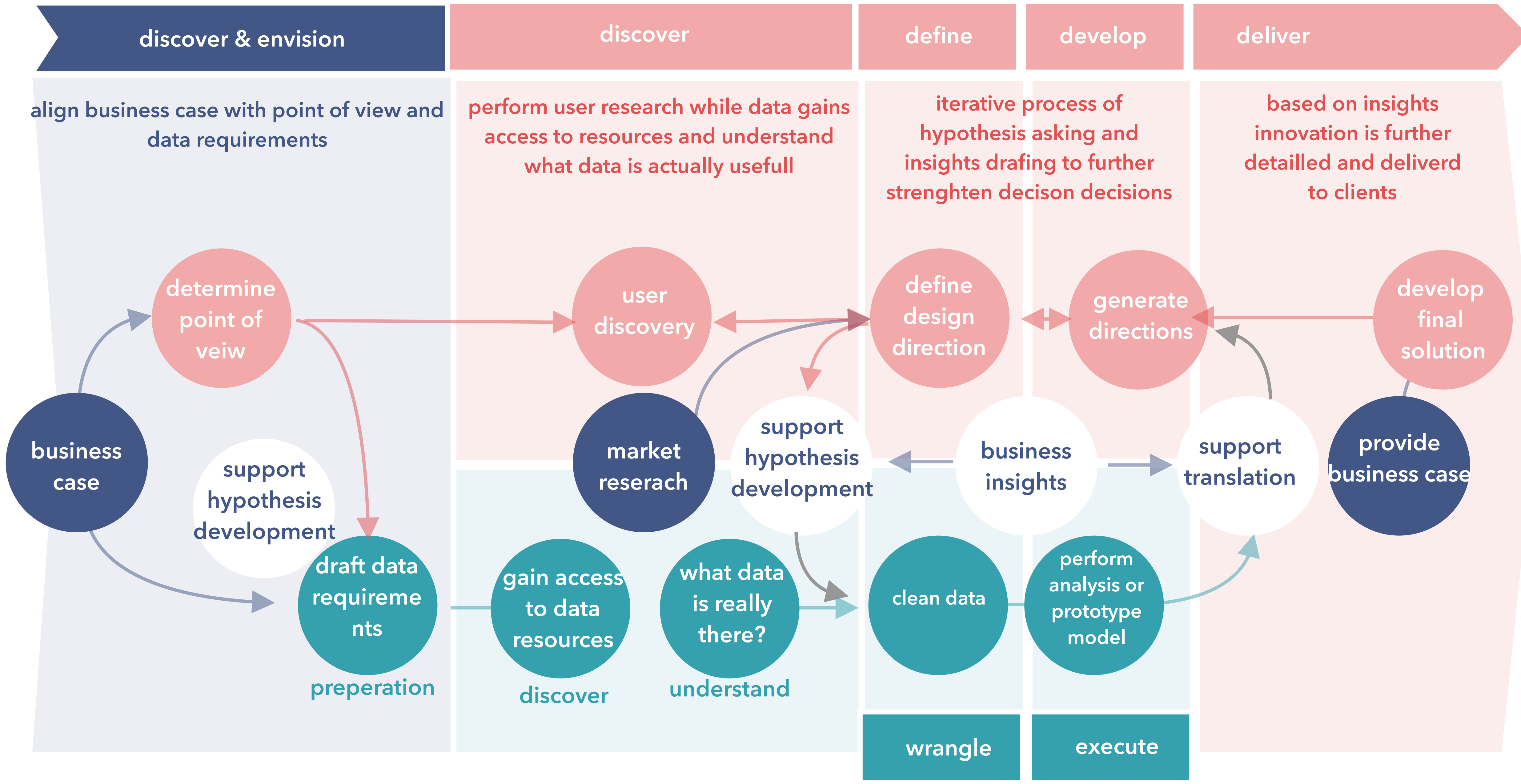


Figure 6.6 - Data-informed design innovation journey - steps of design, strategy and data science.

6.1.3 Profile

To perform the activities, the data-design lead needs to have a profile combined of data science capabilities, service-design knowledge, business strategy experience. Figure 6.7 provides a visual representation of this profile. Next to these three an important personal trait is the ambition to improve one's management skills. The precise level of required varies per element. The levels of skills and knowledge needed is further elaborated by each knowledge aspect and the level of experience (or education) needed to reach the required level.

Personality traits
The skills required to perform the activities demands a combination between a conceptually and creatively strong, and analytical profile. A strong and persuasive communicator, with high emotional intelligence and social skills.

Background
First, business strategy. A background in strategy consulting or corporate strategy is required, with a minimum of seven years working experience. By having experience in business strategy, the strategist is trained in drafting financial business cases and communicating these to clients. A strategist perceives the viability for an organisation as the leading argumentation which directly aligns with the goal of DCF's clients. Second, a lengthy experience in strategy brings a higher mandate around from management. Third, the ability to analyse and diagnose complex issues and making these concrete, for example by draft issue trees, or diagnostic maps are common skills adopted by strategy consultants; aims to enhance clarity, thoroughness and coherence of the analysis (Chevallier, 2016).
Second, data science. Domain knowledge and a statistical aptitude is required, Previous programming experience (e.g. Matlab, Python, R, SQL) acquired either via a master's degree or a minimum of one-two years working experience in e.g. financial modeling is required. Understanding the complexity of models and algorithms is really understanding how analysis is performed, how accurate data and hypotheses are and what concrete results deliver.
Third, service-design. The data-design lead requires a background in service design or design-driven innovation, with a minimum of 1-2 years of relevant working experience. This working experience could be acquired at a service-design agency but also a high chance this is required during earlier multi-disciplinary projects that drove innovation.

Recruiting the data-design lead
However, for successful recruitment, the profile description should be seen as guidelines rather than necessities. First, the drafted profile is based on internal research and thus contains bias, the perspective of the current employees. Second, senior persons tend to have already developed a vision on the precise job design. Therefore the process of job crafting (Wrześniewski & Dutton, 2001) should be included during the interviewing. Job crafting involves employees taking the initiative in customizing their own work to fit their needs, values, skills and abilities (Bakker et al., 2012, Nielsen and Abildgaard, 2012). Rather than forcing the profile descriptions to fit a certain profile, DCFs should use these as guidelines in order to guarantee a successful recruiting process.

Figure 6.7 - Visual representaion of profile

6.2 Implementation

This section elaborates on the efforts the DCFs management need to do to

First implication - business case

This section elaborated the business case behind the new role, from the management points of view. Concluded from the profile drafted in previous section, the profile demands high seniority, high educated background and with that a high salary. Mandate from management is pivotal for the adoption of this new role and financial benefit is perceived as crucial. Performance of the introduction of the new role is calculated by the following metrics; number of extra revenue from data-science projects (constructed from higher effectiveness in opportunity utilization). In appendix 7.1 the financial business case is presented. In this business case the FTE costs of salary are crossed from the financial benefit from this new role; more data science projects. Concluded is that the increase of extra revenue generated from extra data science projects outweigh the costs (decrease of billability of salary hours) of salary of the new role. The two largest drivers are (1) the ability of the person to actually integrate the two teams. This argues to believe that the biggest driver for the success of the new role is the adoption from the job-holder itself. **Concluded from the business case, the highest determination of the success of the new role is (1) the adoption of the new job-holder and (2) the adoption of the decision makers in the data and design team. Actions to increase both are now discussed.**

Adoption job-holder - hiring or position shift?

Although the business strategy aspect is important, it should not lead to the discard of the others. The lowering of the business strategy cannot however lead to a high lowering in seniority. Seniority is found to be highly influential. The data-design lead should initially be aimed to shift from the strategy team towards the new role. For the DCF, an important decision has to be made. Either to find a new hire, or to promote a current employee from the strategy team to the data-design lead. The firm should initially focus on a position shift. DCFs management has argued that a position shift is more desirable due to high onboarding time high. Newcomers in a role are subject to the same processes – thus they will have reduced job content in comparison with existing (competent) employees (Glegg & Spencer, 2007). An important activitiy DCF has to perform is the increase of trust as this is perceived important. Current employees could doubt on the motives.

Adoption job-holder - job crafting

The data-design lead should be provided the freedom to further develop this role from his perception. Jobs with a high level of autonomy, jobholders experience greater personal responsibility for their own successes and failures at work (Hackman & Oldham, 1980). The new role should not be a static design activity, but rather seen as a dynamic and circular process (Clegg and Spencer, 2007) and in such should be iterated and improved by the lead. An important Who is responsible for the future success of the implementation? How do we measure this new role to actually be successful? **An important activity argued by Wrześniewski & Dutton (2001) is job crafting. In general, job crafting involves employees taking the initiative in customizing their own work to fit their needs, values, skills and abilities (Bakker et al., 2012, Nielsen and Abildgaard, 2012).**

Adoption data & design team - Change readiness

The first action to be undertaken is the sharing of the vision on know-why and know-how (Swanson, 1994). The goal of this action is to raise the change readiness (Stanrford, 2007) inside the DCF so that the process is adopted well. This could be in the form of presentations, individuals conversations or sharing of documents. These efforts are aimed at two results: mandate from the management (top-down) and champion employees (bottom-up). These champions (both in the service design and data science teams), are the ones that need to be enthusiastic (Stanrford, 2007), as they are the ones mostly performing the activities.

Adoption data & design team - organisational change

The new role is proposed to be positioned in a cross functional layer, outside of the strategy team (see figure 6.8) . As job design is a social process, concerning a job-holder, supervisors and peers (Clegg and Spencer, 2007) this new position aims to improve the social and cultural adaptation of the new role (mainly of the decision makers in the data and design). This is especially important due to two reasons; non-individual motives of the new role and higher mandate from management. First, because the new role is positioned out of the strategy team towards a cross functional layer, the trust in the motives of the new role increases. Prior, motives could have been interpreted as strategy-team beneficial, while the new position aims to integrate the two teams. Second, because the new role is not funded and performance reviewed by a strategy lead, but rather by management itself, the perceived mandate from the new role increases (Stanford, 2007).

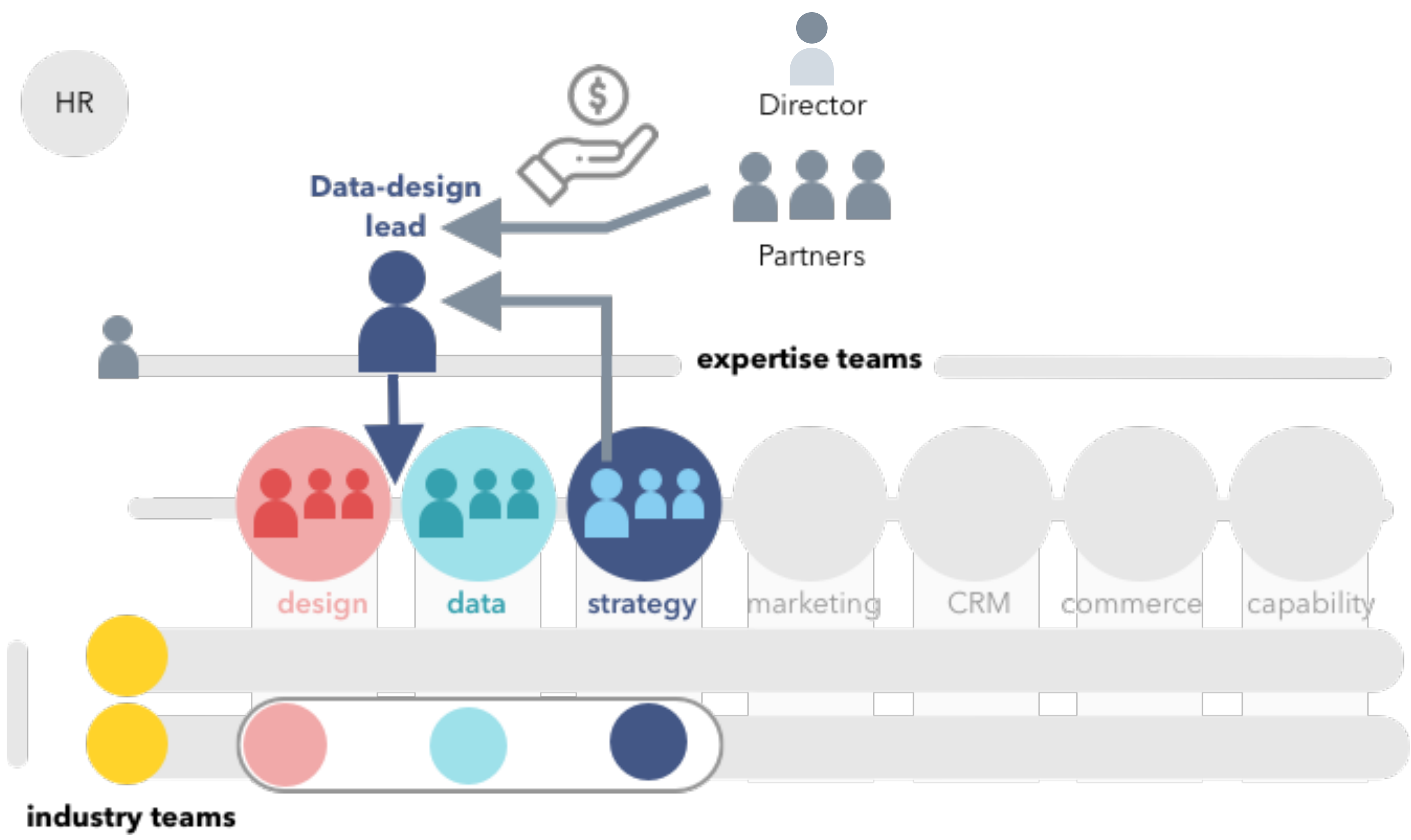
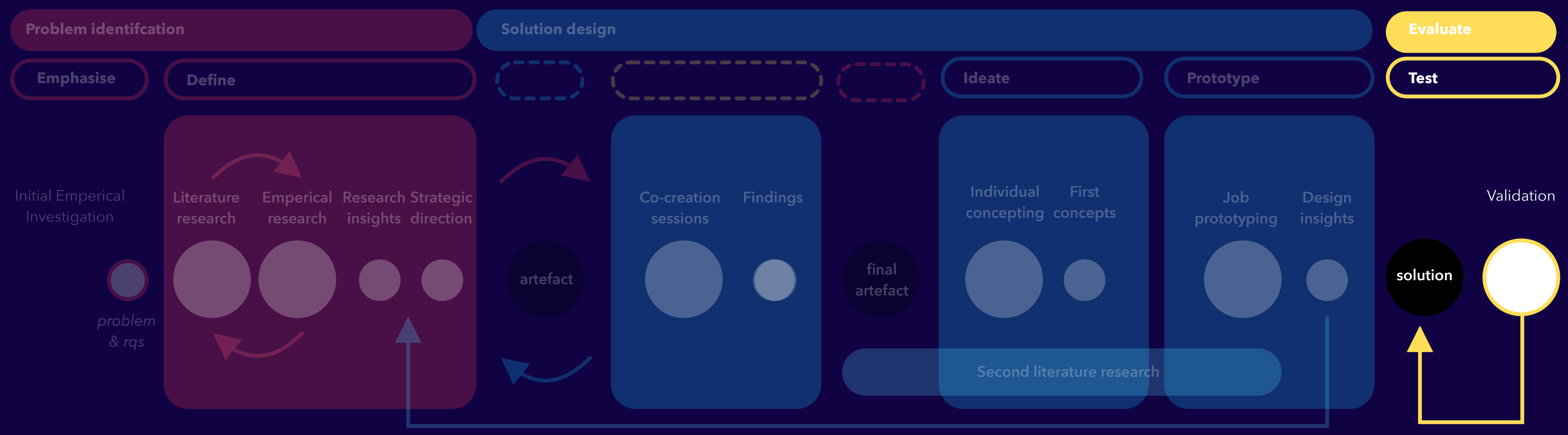


Figure 6.8 - new organisation structure - a strategist is moved from organisation position towards a cross layer of the data and design team

7. Design validation

This chapter discusses the validation study performed on the final solution. During the validation, role playing has been used during a co-creative workshop with a designer, data scientist and strategist.



7.1 Validation study

Validation is essential to evaluate the final designed final concept by evaluating what works, what the actual value is to stakeholders, and understanding the impediments and providing final improvements to the design (Offermann et al., 2009). Throughout the research, three validation activities are performed; co-creation sessions during the define phase, job prototyping during the prototyping phase, and the final design validation during the test phase. This study only included the findings of the final validation. Although comparison with earlier findings could deliver interesting insights (especially the co-creation sessions as the new role was not present), generalizability is too low. Other participants, different roles of the author or different procedures are a few of the factors that constraint this comparison.

This study has five foci; DCFs organisation elements, data-design lead's profile, data science and design team, job holders and meeting design. In table 7.1, the five levels are visualised, the objective of the analysis and the protocol. The validation study is performed in four parts; opportunity identification, decision meeting, business case validation and profile validation.

7.1.1 Methodology

The method of the validation study is based on triangularity with non-participant observations, semi-structured interviews and co-reflection. In addition, the participants are asked to provide feedback on the analysis results (Golafshani, 2003). All participants are purposefully selected. The designer and data scientist are selected as decision-makers in their team (senior position prior experience with proposal drafting and lead of team) and have not participated in prior design activities to reduce bias. The strategist is identified during job-prototyping as a potential job-holder. The business case and profile participants are selected based on their position in the company and expertise on the focus of the evaluation activity. The business case is validated with the firm's strategy lead. The profile validation is performed with the recruiter of the firm.

Foci	Subcategories	Objective of analysis	Protocol
Organisation	Organisation structure, position, business case	Business case validation - is the role a viable opportunity for the firm?	Co-reflection of rationale design and designed materials; organisation structure and business case
Profile	Recruiting, hiring	Evaluating the feasibility of the developed profile for recruiting	Co-reflection of rationale behind profile and persona
Data and design teams	Role, activities, desirability, learning of activity, leadership style	Does the new design enable integration of the teams? Does it facilitate in the right way?	Role play participation during collaborative decision meeting and semi-structured interviews to reflect on role play
Job holder	Self-efficacy, role, responsibilities, activities, promise	Understand if the role is a desirable and feasible one to perform for potential job holders.	Role play participation of potential job holder as facilitator during collaborative decision meeting
Meeting design	Framework, templates, meeting structure	Evaluate utility - do the activities and framework provide value to develop viable proposals	Use of artefact during collaborative decision meeting and reflected on use

Table 7.1 - Five foci validation study

Part of study	Method	Participants	Context
Opportunity identification	Role playing Observations Co-reflection Semi structured interview	• designer - value proposition lead • data scientist - data science lead and • strategist as potential job-holder	Prior to the workshop two activities are performed according to the scenario to simulate the decision meeting in realistic context.
Decision meeting	Role playing Observations Co-reflection Semi-structured interview	• designer - value proposition lead • data scientist - data science lead and • strategist as potential job-holder	Collaborative decision meeting with the intention to develop a client proposal.
Business case	Co-reflection	• Strategy lead	Online meeting presenting business case sheet and co-reflection on assumptions
Profile validation	Co-reflection	• Recruiter	Online meeting based on prior shared profile

Table 7.2 - Four parts of study, method, participants and context

Procedure

To simulate the influence of the new lead and the effect of the activities performed, role-playing is used based on a predetermined scenario. Four validation activities have been performed (table 7.2): opportunity identification and co-reflection, nudging the designer, collaborative decision meeting and semi-structured interviews. Due to COVID-19 and time constraints from the participants, all activities are performed online and done seperatly. To support this procedure, visual scenario is used (see chapter job prototyping).

Part of study	Materials	Time	Foci
Opportunity identification	• Visual scenario • Proposal selection • Online meeting (Google meet) • Google agenda	15 - 30 minute activities	nuding activity, job holder ability
Decision meeting	• Mural board with templates • Online meeting (Google meet)	2 hours	internal alignment meeting decision making process quality proposal draft learning ability person-to-person knowledge transfer facilitation job holder framework (final artifact)
Validate business case	• Online meeting (Google meet) • Business case •	1 hour	viability new role assumptions business case organisation structure position
Profile validation	• Job-holder profile • Online meeting (Google meet)	1 hour	profile feasibility recruiting

Table 7.3 - Four parts of study, materials, time and foci

To simulate the 'nudge' 10 pre-selected design proposals are presented to the strategist. First, the strategist is asked to select the most promising data science opportunity. This opportunity is shared to the design decision-maker and last to the data scientist. All participants are asked to articulating the diagnoses of experience. The second part is the decision meeting. During role-playing co-creation sessions, the participants are audio recorded, a reflective assignment has been performed, and they are interviewed afterwards to reflect on the session. The participants are asked to provide feedback on three levels; self, artefacts and circumstances (Hong & Choi, 2011). To clarify both; artefacts are the tools and templates provided to the participants; circumstances are things like the meeting, time, quality of or speed; self refers to the participant reflecting on one's actions. At the organisational level, the business case and profile are validated during two one-hour co-reflection interviews.

Analysis
The interview's audio recordings are listened back to and are transcribed. A thematic clustering is performed, clustering and categorising the quotes multiple times to find patterns and gather insights to the research questions. Appendix 7.2 provides an overview of the transcribts, families and clusters.

7.2. Findings

This section discusses the conclusions from the validation study. Before all findings are discussed, a short summary is provided.

Summary
The value of the new data-design lead has been perceived as highly valuable by all participants and can be categorised in six capabilities; opportunity nudging, aligning data-design, discussion starter, clarifying alternatives, choosing alternatives and putting business central. The three roles the data-design lead can take (directing, supporting and project-based) are all perceived as necessary to improve the integration maturity of the two teams.

During the workshop, the differences between the two teams were again clarified and the participants were surprised how much they still were apart and how much help was needed. An important implication for future collaborations is concluded; making one of the two teams first violon and the other one facilitating to that.

The job-holder is perceived as highly capable of performing the activities. Although the job-holder perceives the role as valuable to the organisation, he himself would not be interested in this position shift. The job-holder argues that he has a bias towards the doing of projects rather than managing people and facilitating. The importance of good facilitation has been observed as highly influential in the quality of the decision makers and the learning of the participants.

The activities have all been perceived all valuable with two additions; during the nuding the designer would like to be more informed on the data requirements he needs to ask to the client before the discussion meeting. Second, the importance of failication has been strengthened as 'decision power' has been found to be highly influencing the quality of the decision making. Last, concluded from the workshop is the importance of organisation support on the data-design learning and training of both teams. The designers have to improve on drafting concrete hypotheses and the data scientist in creative data analysis in a practical context.

7.2.1 Team level

Value involvement facilitating strategist
The introduction of the new role in the company is perceived by all participants as highly valuable. Based on the validation of the two activities; the nudge and the decision meeting. involvement of the role at discussion meetings is found highly valuable by both participants to enable the decision makers in the data and design teams to integrate both. The designer mentioned 'if the strategist were not present, me and [the data scientist] would have it way more difficult' and the data scientist 'we were able to complement each other because [strategist] was present'. From analysis, six capabilities can be drafted that positively influence the integration between the two teams. Each of these abilities are found to be highly influential in the collaborative decision making process.

'I think if me and [the data scientist] would have sat here without [the strategist], me and [the data scientist] would have it way more difficult' (co-reflection - designer)' '

Opportunity override
Ability to see and communicate the opportunity of integrating data in a design project.
'it is definitely valuable, it triggers me to involve others' (design decision maker)

Align teams.
Ability to get both teams on the same wavelength by communicating in both languages.
'the strategist is able to think both ways and give a reflection on what the other is saying' (designer - co-reflection)

Discussion starter
Coach and support decision makers with suggestions, coaching and challenging.
'I would suggest, choose the five most expensive activities from the operational process, and brainstorm together how we can make those cheaper' (strategist during workshop)

Clarify alternatives.
Ability to make decision alternatives more clear (issue trees, examples and analogies).
'likes piles for the house of a client, you don't see them directly but you need them' (strategist during workshop)

Choosing.
Ability/power to make well argumented choices (convincing) from working experience that unite the teams and steer in the right direction
'If we just start with design, if design could deliver a service blueprint, data science could deliver a cost-efficient analysis' (strategist during workshop)

Business central.
Ability to put client & business goals central and reflect critically on possibilities
'the client value is at least two ways, a better NPS [net promoter score] and lower costs, all our activities that we are now doing should either lead to a better NPS or a better cost reduction, or crucial for a following activity' (strategist during workshop)

Directing - coaching - supporting role along with maturity team integration
All stakeholders involved in the validations, validate the need for the role to decrease over time alongside with the maturity of the integration between the two teams (multi-, inter-, trans-disciplinary). Over time, the specific facilitation role changes (directive, supportive, project-based) along with the maturity of the integration of the data and design team (multi-, inter-, trans-disciplinary).

Directive role: the directive role is found to be ineffective and inefficient for the integration between the teams. 'people are not consciously aware of the collaboration, which enables them to change habits. "To consciously change a habit, people need to establish a new routine and extensively practice it so it can eventually move down into subconscious thinking (Strassheim, 2016)"

Facilitating role: From the interviews it can be concluded that both the data scientist and the designer did not directly increase the ability to integrate the other team. Both mention 'it is not directly into my system' and that 'for the coming 10 times I have to be challenged to seek the collaboration'. This confirms that habit change needs time (Lallly et al. 2010). 'you can see the way we are discussing, that we do this way to seldom, still need a lot of these discussions' (designer during workshop)

Project-based: All stakeholders involved validate that the role of the strategist should diminish over time and be a temporary role. The teams 'should learn this ability' and that 'the leads should find each other better when new opportunities arise'. The role of the strategist however, should depending on the project, be only project based.

Increase maturity - perform projects
Both the participants mentioned that the most important thing for integration is still performing projects. The designer mentioned for real success; make meters with each other, the more often we do this, the more we can learn from the projects. The data scientist mentioned: 'there is only 1 way, a concrete project in which we do this'.

Make meters with each other, the more often we do this, the more we can learn from the projects. (designer during interview)

Differences between teams
During the workshop, the differences between the two teams were again clarified and the participants were surprised how much they still were apart and how much help was needed. To provide an example, the data scientist mentioned user research as an 'client safari (data scientist during workshop)' The strategist mentioned the difference as ''Both a different wavelength and a different granularity' and 'different glasses'. The data scientist directly started with all the data requirements, while the designer started discussing possible solutions 'wait, wait, first I need to write everything down I need (data scientist during workshop).

'but now we are going broader again? We are actually untaught that, because back in the day we were tapped on the finger, because then we lose grip. Proving value is really difficult if things are getting fuzzy' (data scientist during workshop)

Make one first violin
To improve the collaboration, one team should be taken as the project lead and responsible for delivering the solution. The other should be facilitating that process and 'not secretly still want to both deliver a solution'. Data can support design with making better grounded decisions and design can help data with delivering creative input.

'If you want data and design to collaborate, make one the lead, and the other facilitating that process' (strategist during workshop)

7.2.2 Job holder

This section elaborates on the findings of the validations with a potential job-holder. This data is generated in two instances; the nudge (observations and co-reflection) and the decision meeting (observations and co-reflection).

The nudge
The strategist was indeed able to perform a nudge based on the current projects. This insight was made by a combination of business, data science and design knowledge. '[company] project has a large cost-reductive component in it' 'against that background, in practise the weight of a data component is higher' '100 milion cost reduction is actually 100 million profit, 100 million in revenue is likely going to be 5 million'

Problem solution fit
The fit between the issue and the new rol, position and profile are validated by a potential job-holder 'I have performed the [directive] role several times actually and I really see the value of this [supporting] role as katalysator of the integration of the two teams. The strategist mentioned that 'most of the time a project is sold, and after 30% people discover that it is not possible what we have promised the client' and validate the framework as 'that is indeed exactly the process that people need to learn'.
'I really see the value of this [supporting] role as katalysator of the integration of the two teams.' (strategist during co-reflection)

Profile - role alignment: scope down business experience
For him specifically, the new function would not be desirable as 'my motivation is to think of mind-boggling solutions'. Two main reasons for the lack of interest are (1) lack of personal ambition to grow in the facilitating/managing role and (2) the lack of challenge; has done it multiple times and perceives to have sufficient skills. The drafted profile could be too elaborate for the position, as the strategist mentioned 'people with an elaborated business background have a bias towards project details and not specifically a bias to facilitating roles'.

To conclude, the job-holder is perceived as highly capable of performing the activities. Although the job-holder perceives the role as valuable to the organisation, he himself would not be interested in this position shift. The job-holder argues that he has a bias towards the doing of projects rather than managing people and facilitating. The importance of good facilitation has been observed as highly influential in the quality of the decision makers and the learning of the participants.

7.2.3 Activities and templates

The nudge

The nudge activity (ie. the use of a rational override by the data-design lead towards the design decision maker during opportunity identification and evaluation) is perceived as valuable by the designer. The designer mentioned 'it is definitely valuable, it triggers me to involve others' referring to the action. The need for the nudge to continue was further stated as 'still the coming ten times I still need to be helped in identifying these opportunities'. The information the nudge provided (opportunity, brief explanation of opportunity and refer to colleague) however was perceived not enough. The designer needed to be better informed on project data requirements, otherwise the next meeting the designer would have with the data scientist would be inefficient. He would like to 'already ask some questions' to make a data briefing 'that the data scientist already has a better picture, what are the possibilities regarding data'. Second, there was a distinct difference between the two nudges presented; the first one inspired to do action while the second one did not. The two main given reasons; non-perceived added value of data science team and timing of the nudge. 'include data so we can sell a data project? I did not even start with the design project'.

'it is definitely valuable, it triggers me to involve others' but he further needs data requirements 'that i already can ask some questions, that cornelis already has a better picture, wat are the possibilities regarding data'

Decision meeting

The value of the meetings was perceived by all participants. The designer mentioned due to this session, he did better understand how data science can support his design work in a specific situation 'now I can ask data to support my design choices better with data, by using the scrabble word [the strategist] used'.

I find the discussion really valuable, actually after this session I think, let's just do it' (data scientist - co-reflection workshop) 'really valuable to sit with a group like this'

Decision power

Observed from the workshop 'decision power' as an important mechanism has been found. The decision process during the workshop is found to be more complex than initially thought. The data scientist mentioned: 'little bit of fighting, little bit of being dominant and then we always draft an approach' The decisions made were highly dependent on the level of discussions, the participation of all participants in those discussions, the amount of weighing alternatives against each other, persuasion and last decision power. This latter, decision power has been found to be increased by four things; expertise, experience, communication skills and participation. This finding implicates that the facilitating role of the lead is extra important to guarantee quality decision making. However the strategist mentioned that 'I am still struggling to find my role, should I think along or just give comments on the input of both' and observed that the data scientist, during fifteen minutes was not present in decision making. 'oh sorry, in my head I already pulled those apart'

'At a real proposal, this is also how it goes. If we are with three or with ten persons, eventually one person has to say this is how we are going to do it' (data scientist during interview)

Templates

One of the templates was perceived as valuable for collaborative decision making. The first template however was perceived as too difficult to work. While the process visualized the way-of-thinking, the more linear template if found to provide more structure to the participants to make order of steps. The designer mentioned 'It works a lot easier to write the process more linear'. The data scientist further argues 'The digital collaboration with the templates and post-it really were in beginning difficult to start using, but at the end it worked really well'

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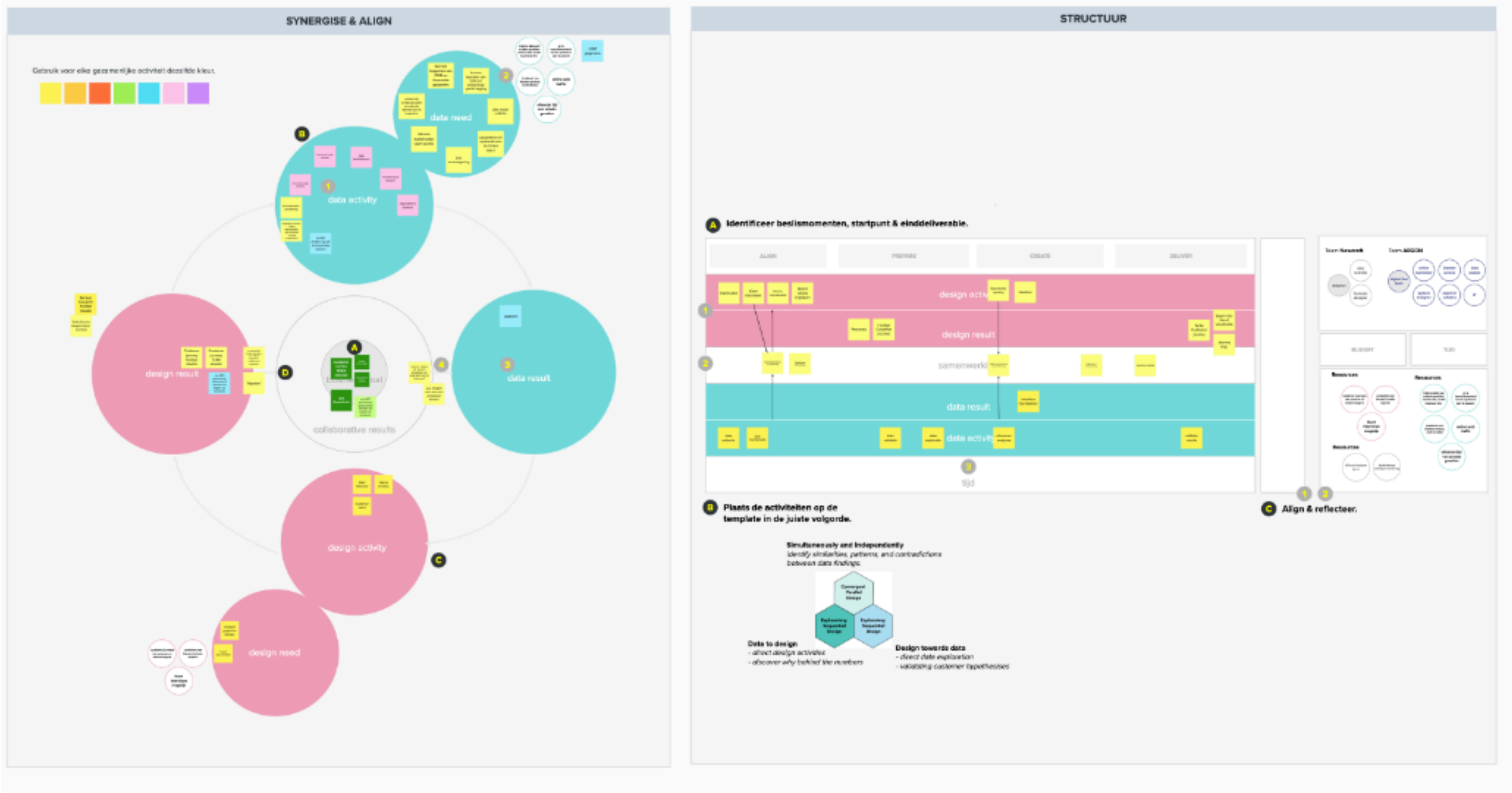

8. Discussion

This final chapter shares the discussion of the research, reflects on the role of designers based on the research finding and provides the implications for the research fields and limitations of the project. The chapter concludes with a personal reflection.

8.1 Recommendations

This thesis aimed to explore and design practical support for a digital consulting firm (DCF), to integrate data science in their current design approach to innovation. This is done through literature research, empirical research, design and evaluation of artefacts, ideation sessions, job prototyping sessions and the design and validation of a solution, 'the data design lead'.

The research argues that integrating data science in design innovation through data-informed design is a viable opportunity for the DCF. It is strategically aligned with current resources and supports the growth strategy towards large enterprises. Findings suggests using data science for design innovation increases the DCF's designers' ability to quality innovation client projects, to argument design choices and to acquire design innovation projects.

The firm can facilitate this integration by using a formalized and personalized knowledge strategy. This strategy supports data-design integration by resolving practical issues caused by the DCF's matrix structure, expert economic model and pragmatic culture. The firm should institutionalize an internal alignment meeting. This meeting supports the data and design team's decision-makers to exploit opportunities better, increase the number of collaborative projects and decrease the risk of overhead costs. In addition, a framework is proposed to be used during this meeting, supporting the interdisciplinary decision making and analyzing process.

The solution argues that the firm should create a new role in the organization, 'the data design lead'. This role transfers the leads' data design innovation expertise by facilitating the meetings, nudging the decision-makers to increase opportunity identification, and participating in data-informed design projects. The role is validated as desirable by employees and as feasible to the recruiter. In addition, a business case validating the lead increases revenue by cross-selling data scientists on design proposals and suggests the introduction of the lead decreases the risk of overhead costs. The firm is recommended to create a new due role position in the organization structure by either reposition someone from the strategy team or recruit the right job holder. A profile is drafted to support the recruiting process in line with the role's responsibilities, the firms' company-culture and work ethics.

Although both the employees' desirability and financial viability are validated, concerns remain over the willingness of management to hire a new person. Hiring a new person could be a threshold for management. For this reason, the following three questions are answered; what activities are recommended to the data science and design team to enable integration if no person is hired? How should this integration be facilitated? Where should the leadership of this facilitation be? This section recommends six activities that the DCF and its decision-makers could perform to facilitate data-design integration without hiring a new person

Activity 1 - Develop framework for collaboration
The decision-makers should be supported with opportunity development by creating data-design innovation propositions. The decision-makers should use the internal alignment meeting and the proposed data-design decision-making framework to identify linking deliverables between the teams. The design team can share their service offerings on which the data science team can generate supporting activities. In addition, a more fruitful approach could be to let the data science team share the activities they can perform and let the design team think of applications as current service offerings. The propositions should be captured in a template consisting of five elements: (1) what is the design service offering (2) how can data science support this offering (3) what person should be the knowledge keeper of this service offering (4) expected resources and project costs and (5) an example of a case. The proposals in the framework support decision making during three furhter activities: opportunity identification (activity 2), requirement meeting (activity 3) and internal alignment meeting (activity 4).

Activity 2 - Opportunity identification & performance review
To support the DCF's decision-makers with opportunity identification, passive rational overrides are recommended to implement. These rational overrides consist of three activities; opportunity sharing (pre-opportunity), opportunity identification and performance review (post-opportunity). First, the data-design opportunity framework is shared to both the data and design team's decision-makers. This meeting aims to let the decision-makers create a self-commitment to create an 'extra decision point' during opportunity identification. These commitments should be detailed and action-oriented (Hansen & Jespersen, 2013). The commitment is aimed to include an extra decision point, during which the decision-maker should rationally think about the possibility of data-design collaboration (based on the opportunity framework). After projects or proposal delivery, during the same meetings, the decision-makers can evaluate the actions made and show performance relative to others (Hansen & Jespersen, 2013) and provide personalised feedback (Frsysak, 2016).

Activity 3 - Requirement meeting
When a decision-maker has identified an opportunity (with the proposal framework) and the 'knowledge holder' is informed, it is recommended to have a requirement meeting before the actual draft of a proposal. This meeting aims to review the initial briefing and identify the project requirements. The meeting is proposed to be short (± half hour) to make a call on intuition; this allows to be both efficient and filter out any potential alignment meetings that would have been a waste of time. To refer to the decision making process proposed in chapter 4 (see figure 4.4), the first three steps have to be performed during this meeting; (1) review initial proposal, (2) determine project constraints and (3) determine project constraints. The result of these meetings should be a simple go-no-go.

Activity 4 - Alignment meeting
The presence and facilitation of a data-design expert allows a transdisciplinary approach to assessing client challenges by a comprehensive assessment together (Nicholson and Armitage, 2000). Without this person, the teams initially are unable to make comprehensive assessments or develop offerings together. They should instead initially focus on interdisciplinary assessment of clients needs, i.e. separate assessment but with consultation from other teams (Nicholson and Armitage, 2000). The internal alignment meeting is in consultation with each other.

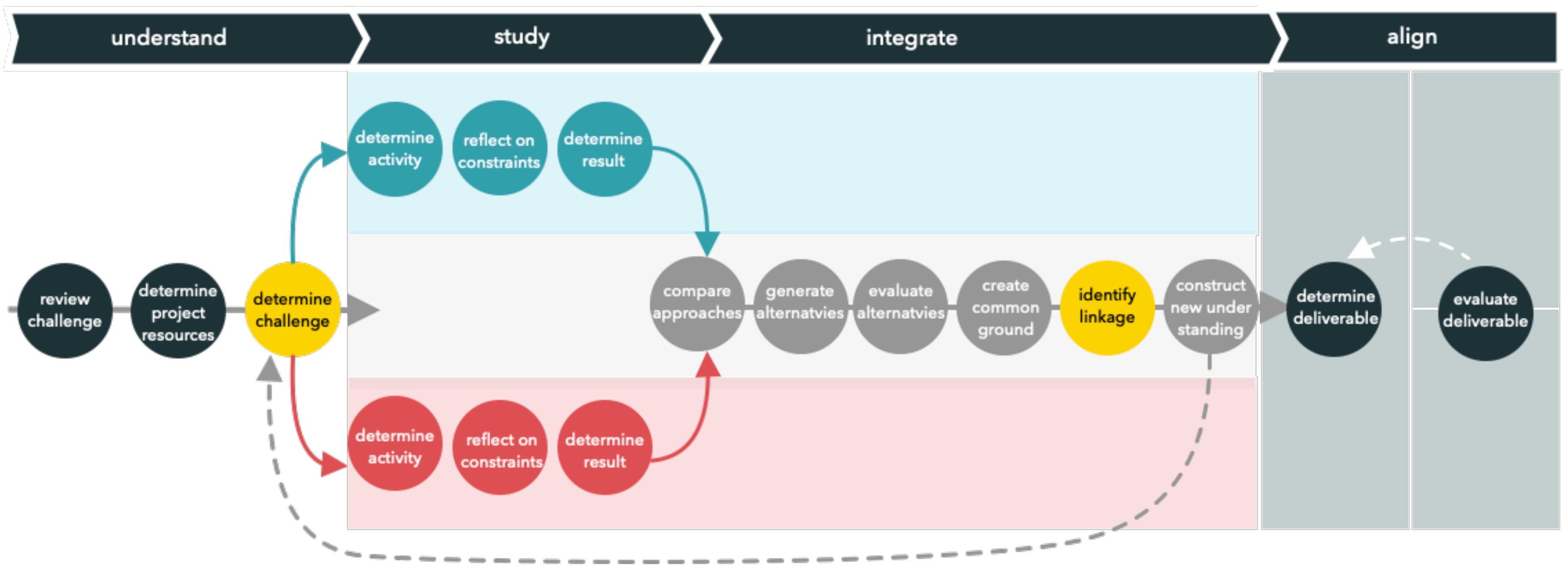

Figure 8.1 - Data-design decision making process - visualised on proposal framework

Activity 5 - Training program development
Further, the teams cannot directly learn from a person who has the ability to diagnose data-design client challenges well. The research suggests both need to learn to: view the client's challenge from both a data science and design innovation perspective, think comparatively between those and balance internal feasibility with the client's desirability. This means they must develop this ability by themselves. Training programs are a valuable approach to knowledge development inside organisations (Stanford, 2007). Based on the research findings (see 4.2.4 Learning), the following training programs are recommended to be developed; (1) Data science training for the design team: focus on learning data science domain knowledge and hypothesis training. (2) Creative use of data training for the data science team: focus on abductive thinking and impact effort practise (3) FTE & cost calculation training both teams.

Activity 6 - Collaborative learning meeting
To support the integration, the teams should increase their effort in learning themselves. The team members need to make a more considerable commitment to teach, learn and work across teams, and the employees need to be developed across disciplines to align (Nicholson and Armitage, 2000). It is recommended to introduce monthly team meetings between the data and design teams. Sharing the right knowledge before decision are improves collaborative decision making (Arduin, Grundtstein & Rosenthal Sabroux, 2013). In these meetings, employees can share learnings and make these learnings themselves.

Conclusion
To conclude, this section recommended six activities that the DCF and its decision-makers should perform to facilitate data-design integration without hiring a new person. These activities suggest that the teams need to make a more considerable commitment to teach, learn and work together and perform more cross-team meetings (Nicholson and Armitage, 2000). However, they cannot do a comprehensive assessment of clients needs and cannot develop service offerings together to exploit opportunities (Nicholson and Armitage, 2000). This suggests that while the effort increases, the potential output decreases. Empirical research argues that this causes a higher chance of missing opportunities (and revenue) and higher overhead costs. Based on these findings, the business case is recalculated. Although not validated, the findings suggest that the costs are higher (many more hours of individual employees' efforts) and lower revenue (lower conversion rate of cross-selling data science projects. From this perspective, it is suggested that although management perceived financial risk in hiring or repositioning a person to the data-design lead, not hiring one is a more costly direction.

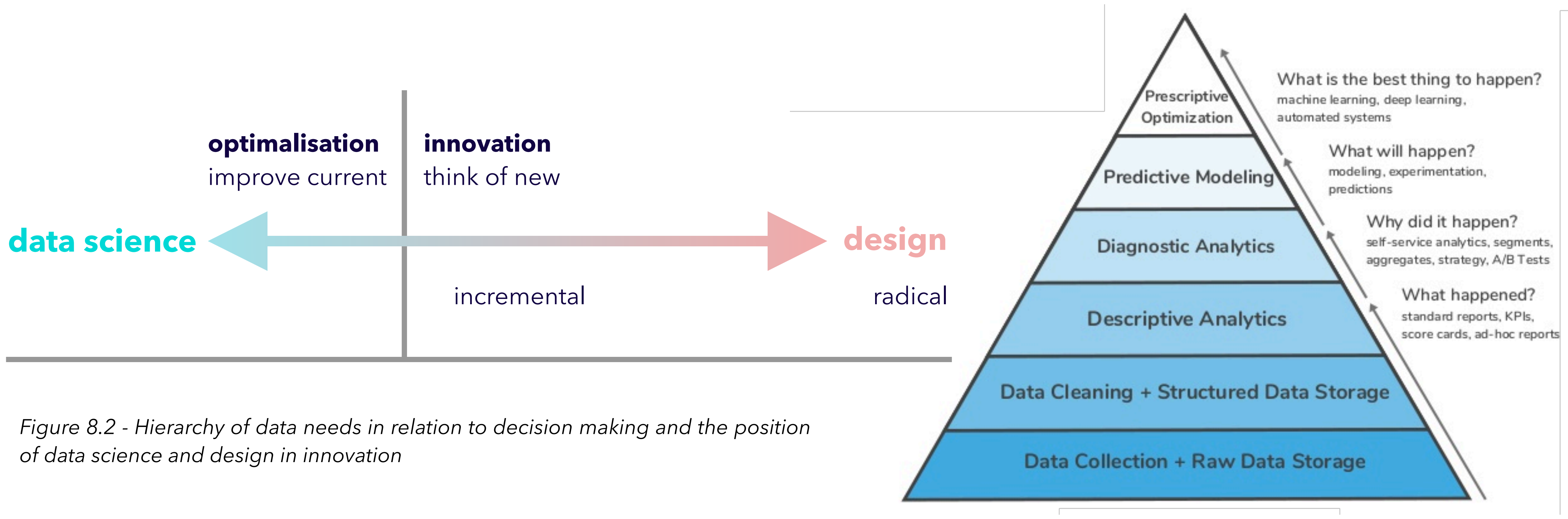

Figure 8.2 - Hierarchy of data needs in relation to decision making and the position of data science and design in innovation

8.2 Role designer

This section reflects on the research and aims to provide an answer to the last research questions, 'what could the future role of designers be in the future of innovation?'

Data science is often related to optimization of current activities. Clients mainly are willing to apply data science if there is a cost-reductive nature to the project. This is quite logical because improving something that exists (in many cases) has more data to do so. However, Innovation implies thinking of something new, something that does not already exist. A recent paper by Verganti (2020) argues that AI (Artificial Intelligence) not only incorporates the three essential principles of design thinking but outperforms human- centered innovation by eliminating human- intensive limitations. This thesis places a critical note to the generalizability of these findings, which are interesting enough, the most common used examples of data design innovation by participants in the research. These almost magical data science abilities are not comparable to current organisation's practises and only tend to increase the 'data science blackbox'. The research suggests that data can provide information (i.e. data-informed design) for innovation but the direct answer (i.e. data-driven design). To refer to hierarchy of needs (see figure 8.2) knowledge pyramid, the level of information provided with regard to innovation ist still at the information level - ie. what happened? In line with previous authors (Ngai, 2016; Huang, 2016), this thesis suggests that designers' abductive reasoning and designers' intuition is still essential to provide more context to data findings. Especially in the case of radical innovations, the design intuition is essential to develop valuable innovations.

However, for the discipline of design and design practitioners aiming to play a fundamental role in both radical and incremental innovations, a higher aptitude to data science is needed. In line with the same authors that suggest intuition is still essentially valuable (client interviews and trend research) this thesis suggest that quantitative insights need to become a part of designers dailly practises. It enlarges product and user understanding, increases the quality of innovation decision made and ensures that these decisions satisfy stakeholders. For designers aiming to work with data, four activities are recommended.

1. Increase your ability to draft concrete hypotheses on possible design choices and know which metric you are aiming to validate with that assumptio. This allows to ask the right questions to data scientist and achieve synergy between qualitative (user) insights.
2. Increase your data science domain knowledge. Know for what type of design practises, what type of data activities apply and what data is needed to deliver a valuable insight. This allows to know when to ask a data scientist to validate a certain hypothesis while knowing a valuable insights can be provided.
3. Increase business economics understanding. This latter one is specifically important in the context of consultants of other professional service providers. Knowing what the financial added value of a data-design activitiy is, allows you to communicate this to clients (which are often profit driven) and to provide the possibility. value data-design activities deliver to businesses but also the costs that are related).
4. Practise. In addition, practise is argued to be the most effective route to learn these. Designers are recommended to find a context where opportunities are provided. Based on segmentations made, most organisations are not ready to effectively apply data driven insights in current business operations, let alone use it for innovative purposes.

Although the intersection between data science, design and innovation is an immature one, this research suggests that the combination can play a vital part for organisations to differentiate from competitors and drive business performance. Designers should open the data science blackbox, and explore the opportunities. Not to lose, but to further strenghten their design intuition.

8.3 Contribution to research

This section discussed the research findings and the answers on the research questions related to the existing literature on four levels; the data design integration, the facilitation of that integration, decision-making, and last leadership for innovation.

8.2.1. Data-design integration
The research argues that the DCF can integrate data science in design innovation by data-informed design. This is in line with prior literature that intuition is still valuable and those qualitative insights can be complemented with quantifiable data Ngai (2016) by using data to test and evaluate assumptions and hypotheses (Huang, 2016).

In contrast to authors (Verganti et al., 2020) claiming that AI can outperform design innovation, this thesis argues that data-informed design is more applicable in the practical context of consultancies and non-big tech-driven organisations. Found in the research, data science is often a black box, and where the hierarchy of data needs is not understood well (2.1.2 Big data and data science). A common misconception is the use of examples like Airbnb, Netflix and other large tech-driven organisations. This implies that the type of information that can base design innovation decisions consists of; what happened and why did it happen?

In addition to current literature, practical issues are discovered that are problematic for integrating data science in innovation at DCF. First, the practical context of DCFs customisations economic model and correlating pragmatic culture implicate an ad hoc process that constrains the sharing of knowledge and innovation. Second, the data-design integration is dependent on the budget of the client and the data availability. In addition to the proposed data science process by Gandomi and Haider (2015), the data has to be transferred from the client to the DCFs internal data infrastructure. This can cause technical and legal issues that constraint the development of using data. Further, in theory, combining big thin data with thick data is promising; in practice combining these insights requires more planning and often is not entirely possible. This finding is in line with Pardi (2010) that argued 'often data does not support the design'.

8.2.2. facilitation and leadership
The research proposed that a personalised learning strategy should facilitate data-design integration in the context of DCFs. This is in line with prior research performing in consulting firms (Dunford, 2000). In line with prior research, the lack of management support is problematic for learning and innovation in consulting firms (Weiss, 1999; Dunford, 2000; Taminiau, Smit and de Lange, 2009).

A new meeting is proposed to facilitate a newly introduced role, the data-design lead, and the DCFs data and design team's decision-makers. This is in contrast with prior research regarding leadership in consulting firms. Taminiau, Smit and de Lange (2009) argue that informal knowledge sharing provides the most fruitful route to innovation in consulting firms and only a shift in mindset and culture is needed (Weggeman, 2004). This research proposes that the formalisation of knowledge sharing is necessary. In the instance of the DCF, even if the management changes its 'vision on how knowledge should be shared' this does not lead to actual knowledge transfer. This inline with earlier knowledge leadership research (Nonaka and Takeuchi 1995; von Krogh, Nonaka, and Ichijo 1997) that argue that top managers to act as knowledge leaders should form 'Ba' and direct, promote, and justify the SECI process. The creation of a place for knowledge sharing or 'Ba' (Nonaka and Konno, 1998) in this research is thus the proposed meeting. This proposed meeting allows a person to person knowledge transfer between the formalised lead and decision-makers. Because the decision-makers are actively involved in the decision making, the collaborative decision making improves, which in turn leads to more collaboration and thus more learning.

In addition to current leadership research in consulting firms, the Situational Leadership model of Hersey and Blanchard (1969) is used to align the leadership style with the integration maturity. Three leadership styles are linked to support the data-design integration maturity; a directive style for multidisciplinary, a supporting style for interdisciplinary and a project-based leadership style for transdisciplinary.

The proposed data-design lead also is an addition to current knowledge development research in consulting firms. Although day-to-day knowledge is still perceived as most valuable, the research findings suggest hiring new employees is a common source for acquiring new knowledge. This is in addition to current literature suggesting either can acquire knowledge on the job experience or internal knowledge development (Løwendahl, Revang and Fosstenløkken, 2001).

8.2.3 Knowledge system
The proposed data-design lead also is an addition to current knowledge development research in consulting firms. Although day-to-day knowledge is still perceived as most valuable, the research findings suggest hiring new employees is a common source for acquiring new knowledge. This is in addition to current literature suggesting either can acquire knowledge on the job experience or internal knowledge development (Løwendahl, Revang and Fosstenløkken, 2001). In addition to the organisational learning system proposed by King and others (2009), the research findings suggest that decision-making is an enabler for an organisation's innovation capacity. In addition to learning from collaborative decision-making or learning to make collaborative decisions, decision-making allows collaboration and facilitates learning. The thesis proposed a process between data scientists and designers during interdisciplinary decision-making processes and the necessary analysis to support these decisions. In addition to the two-part interdisciplinary decision-making process proposed by Newell (2007, p248), one particular step is determined for the decision success - the identification of linkage between the two disciplines. A well-chosen link directs both previous activities and future activities. Further, one cognitive ability is essential during interdisciplinary decision-making - the ability to view the (client's) challenge from both a disciplines perspective and think comparatively between those while balancing the firm's internal feasibility with the client's desirability.

8.2.4 Organisation design
The research found that to influence the decision's makers behaviour over time; rational overrides can be used. A rational override is a small moment of intentional friction that attempts to influence people's behaviour or decision-making by intervening in automatic thinking and activating reflective conscious thinking (van Lieren, Gallabretta & Schoormans, 2018). These findings could provide an exciting direction for further research to increase the applicability from rational overrides in service design to organisation design.

8.4 Limitations and future research

Regarding scoping, four limitations need to be mentioned. First, early in the research, the choice is to focus on the design and data science team, not the strategy team. Argued was that the most considerable friction is between these teams. The strategy team, however, during job prototyping, is found to be a potential bridge builder. Altough included in the final design validation, a more lenghty study can provide a deeper understanding of this role. Second, the research primarily focuses on service design; UX and UI were out of scope. However, during research, these designers have indicated that designers' data-driven decision-making and visualisation is a fruitful direction for further research. The question remains if such research still would emphasise a personalised knowledge transfer or that technological infrastructure (because of digital design) would be more applicable. Third, regarding the scope taken to the clients. The interviewees, although from different sized enterprises, are all based in the retail industry. Argued by management and based on the current client base, the retail industry would provide the most promosing direction for the DCF. Interviewing non-firm clients and other industries could provide a better understanding and potentially different results. For instance, the budget and data constraints are argued to constraint data design innovation projects. Are these factors similar in other industries? Last, the integration of design practices for data science activities is also suggested to be promising. Data visualisations and user research are two of these activities. Further research could research the role of design in data science to explore these directions.

Evaluation of the solution's validation sessions provided many insights into the positive influence of introducing a new role. Role-playing provided a new opportunity in the absence of tangible product design (i.e. the job). However, the current analysis is based on one ½-hour online meeting session and qualitative based. In practice, these meetings could take four hours to deliver a valuable proposal. A more lengthy study based on inquiries over more instances is recommended to understand the effect of the data-design lead fully and further strengthen the business case that underpins the introduction of this role. Although a business case is drafted and validated, a more quantitative study can provide a more detailed view, especially important for the management of consulting firms.

Last, most of the research is performed through online video calls. The tools and methods have all been adapted to suit these digital contexts but have potentially missed out on potentially exciting insights. A study in real life can provide new insights and potentially could be a basis for comparison to provide more insights into the impact of digital environments.

8.5 Reflection

In this section, I will reflect on the thesis. From a personal point of view, exploring how we as designers can strengthen the field of design with data science feels a crucial activity to undertake. During my study period but especially during my internships at consulting firms, I sometimes witnessed the lack of innovation power of just 'Strategic Design'. Sometimes it was simply put off as 'fun ideas'. On the other hand, according to Harvard Business Review, the role of data scientists has become "the sexiest job of the 21st century". And this is noticeable in the popularity of data and computer science studies, job directions and even conversations I have in daily life. But when someone asks me what data science is, most of the time data science feels like a magic black box that can answer all the questions along if you are creative enough to feed it the right questions. For this reason, I wanted to increase my knowledge in data science, to strengthen my position as strategic designers and become a more relevant professional.

Prior to graduating I drafted two goals: 1) increase my data science knowledge and 2) increase business design knowledge. Both to be extensions of my T-shaped profile. First I perceive data analytic capabilities as necessary to be more relevant as a professional in this digital age. Second, my current skills are strategic but mostly qualitative, I thought I need to acquire more quantitative skills.

To start off with the biggest, unexpected hurdle of the research; COVID-19 virus. I must admit that initially working from my room came quite easy for me compared to fellow students. However, working towards the greenlight meeting (and probably during the greenlight meeting) I discovered an important insight in my approach to working; my academic writing needed a big refresh. Or hopefully was, considering that you just have read the whole thesis. For this reason, I drafted another goal: increasing my skills in academic writing. I changed my writing approach, wrote quite some literature and step by step have increased my writing skills. However, I believe my strength as a researcher and designer comes from interpersonal communication, not writing. For me, face-to-face interviewing, arguing about potential direction, really getting to know customers' needs, facilitating brainstorming sessions with large groups are all things that give me energy. All these things were constrained to video calls and online tools like Mural. Four weeks prior to delivering the thesis, I was finally allowed to meet the team at the company's building. During several small talks, I discovered so much new knowledge that a video call cannot capture. I believe I do have taken the most out of the resources I have, but still think much of the insights, direction taken could have gone differently if I was able to do it face-to-face.

First, my data science knowledge has increased to a level I am satisfied with. I have reached this level by doing an online data science course, extensive literature study, and many interviews with data scientists. Based on these activities, I now have a more elaborate understanding of the domain, how to talk to data scientists, and what questions to ask. This latter is the most important skill a designer can have - drafting the right hypothesis during research. Although I know what type of questions to ask, I have not done it myself in practice. This is mostly due to the qualitative nature taken in the research. Although, in my perception, the 'black box of data science' is now slightly opened for me, I aim to increase this knowledge after my graduation thesis.

Regarding business design, I made a conscious choice to scope down my expectations of learning business design (on top of data science). Although I haven't directly focussed on the business design itself, I think the data science knowledge is (maybe even more) valuable. In my perspective, business design is multidisciplinary, on the intersection of business, design, economics, but quite important to assume, also data. I think an even stronger position to be in as a designer in the strategic field is understanding how to work with data for business. I believed (and luckily still believe) that this is an important skill to have in the future of innovation and to achieve impact on businesses.

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Appendix

Appendix 1 - Visuals of showcase
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Appendix 3.4 - Findings emperical research - conditions and dynamics
Appendix 3.5- Artefact - framework
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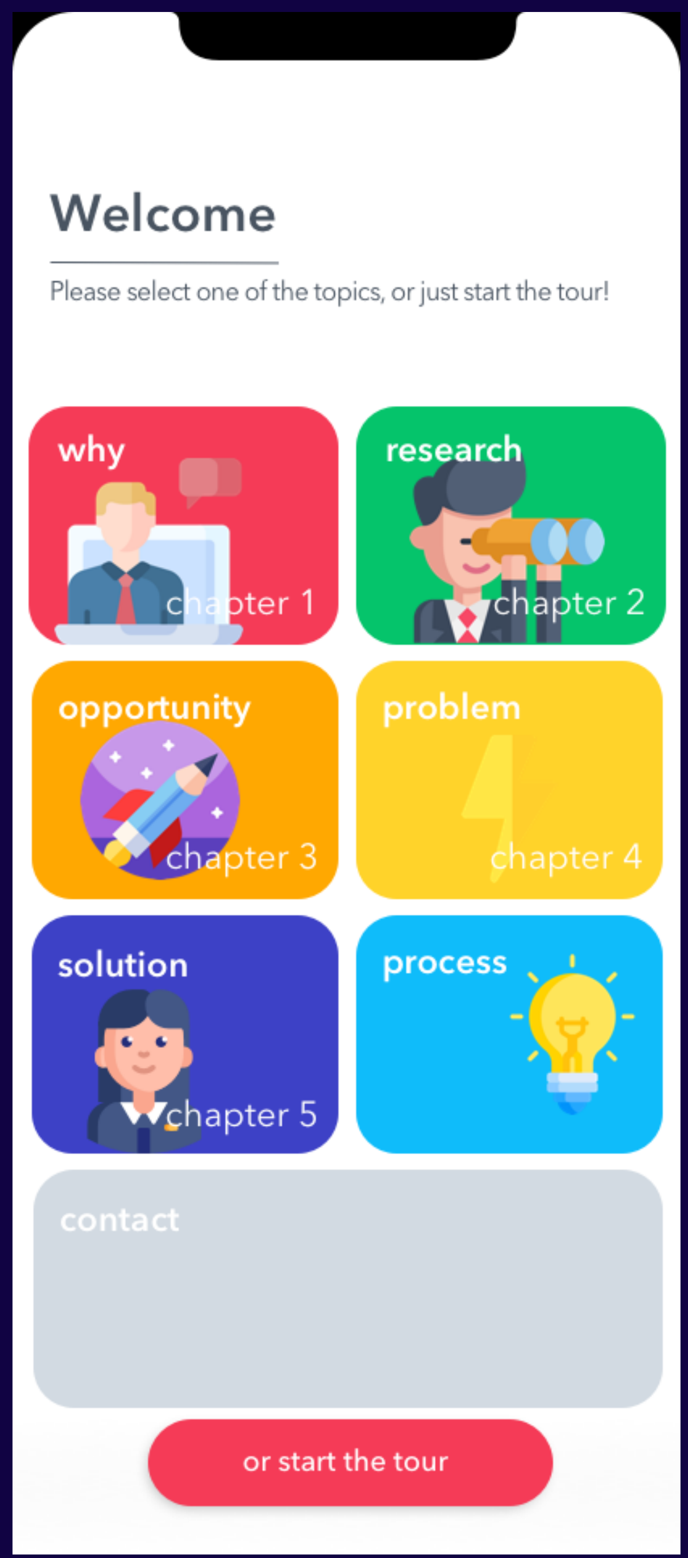
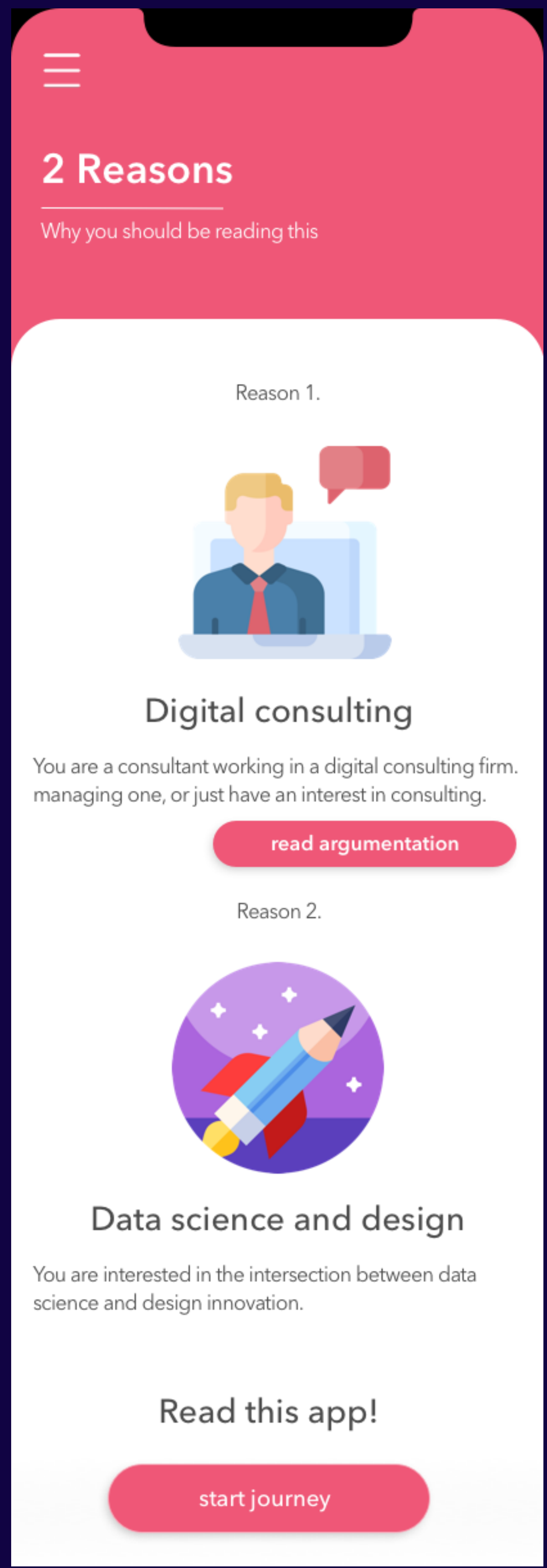
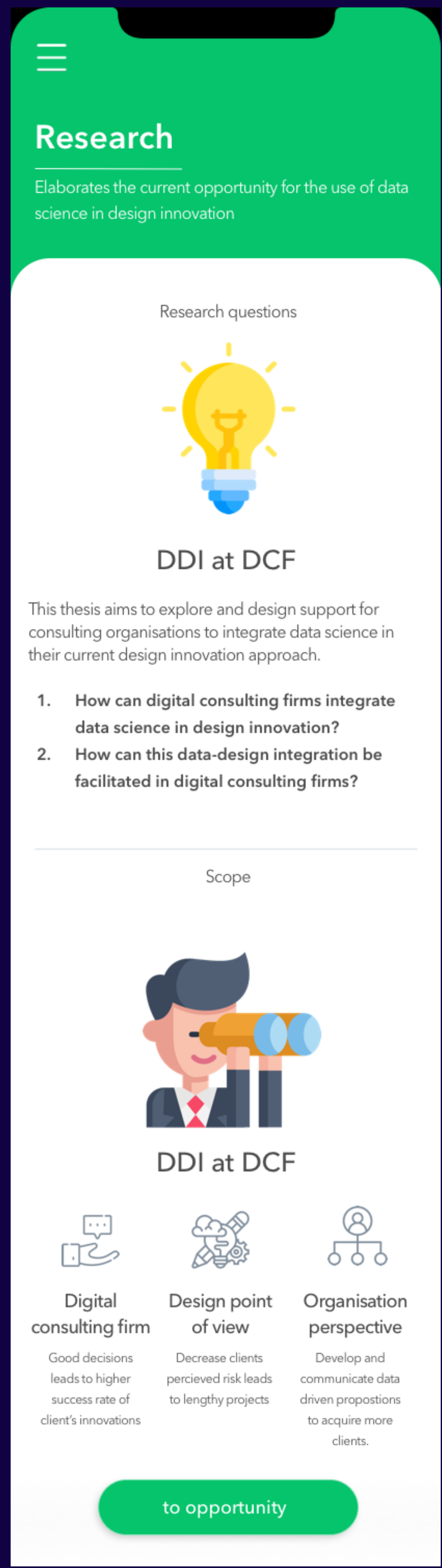
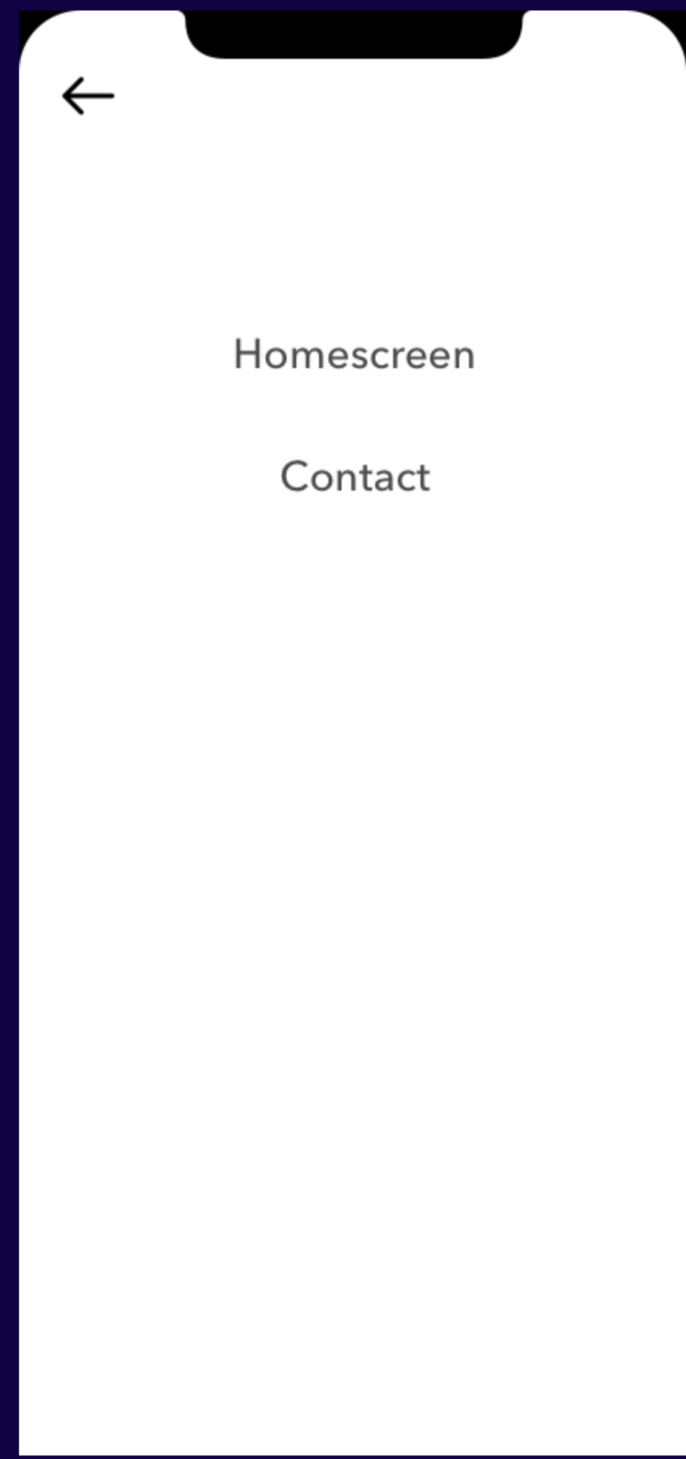
Appendix 1 - Visuals of Showcase

This appendix shares the designed screens of the application. The application serves as showcase for the graduation thesis.









Appendix 1 - Visuals of Showcase

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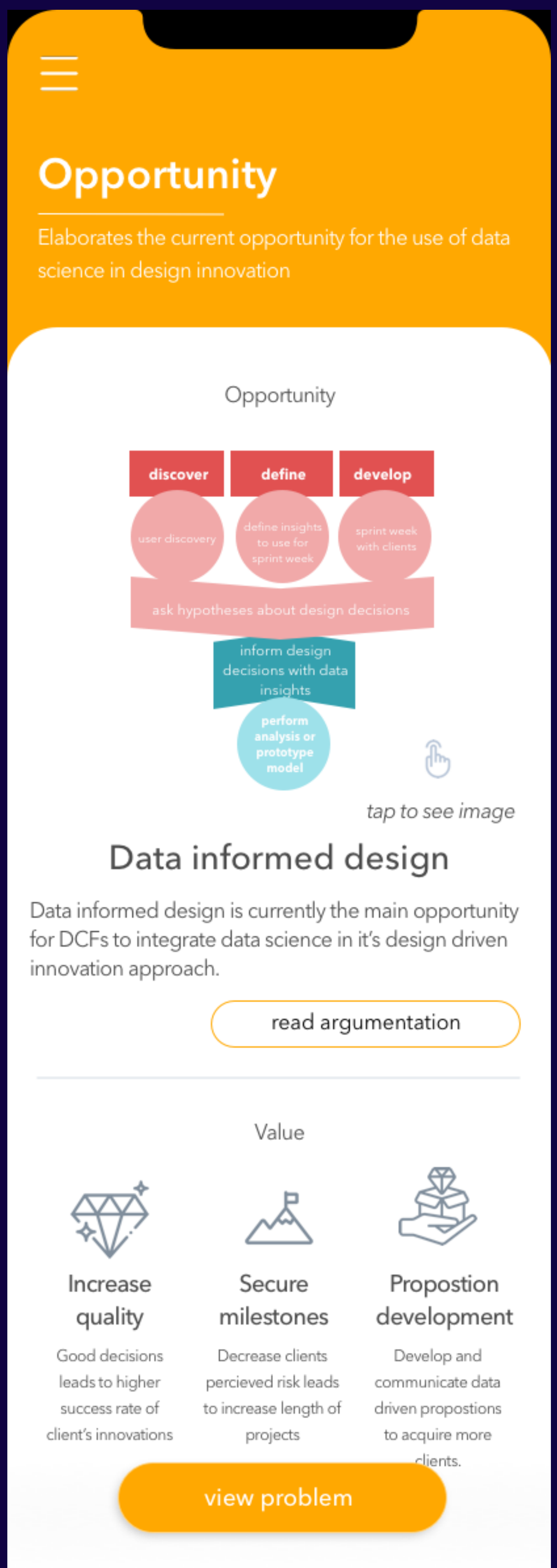

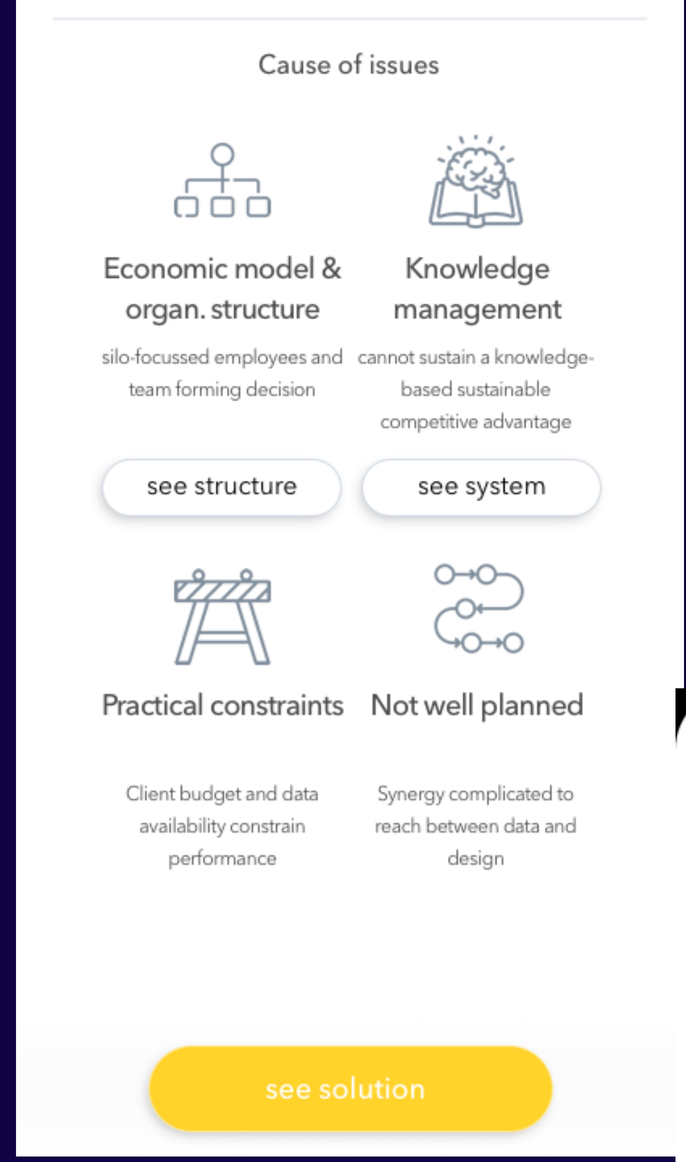

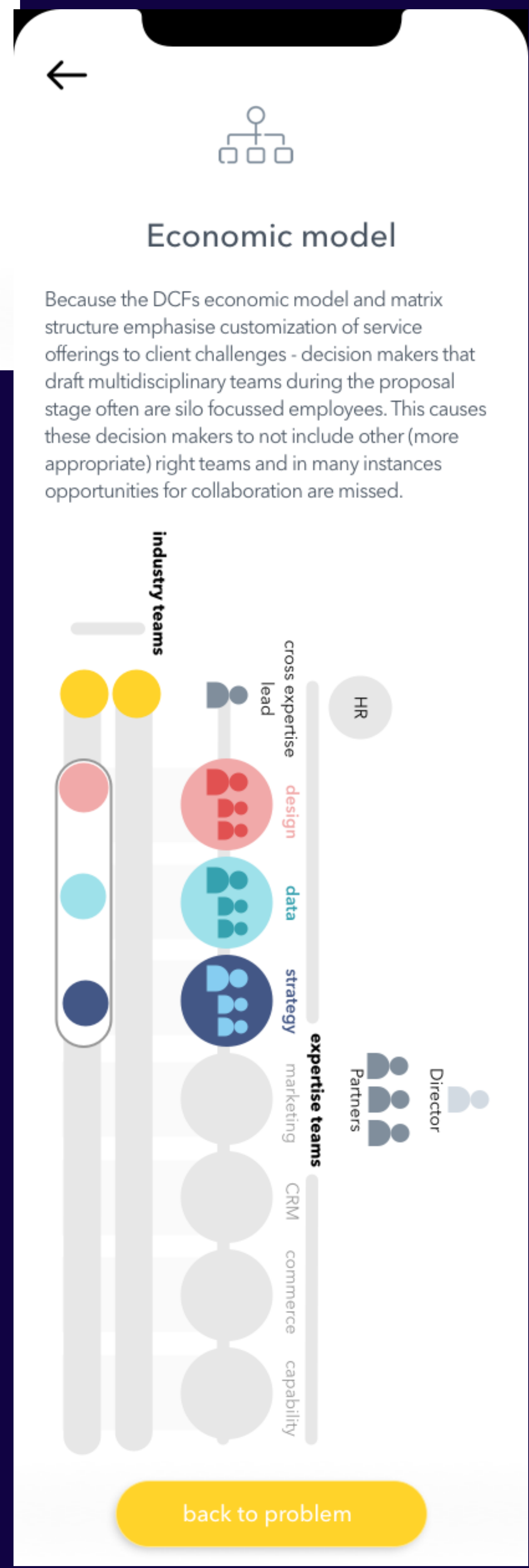

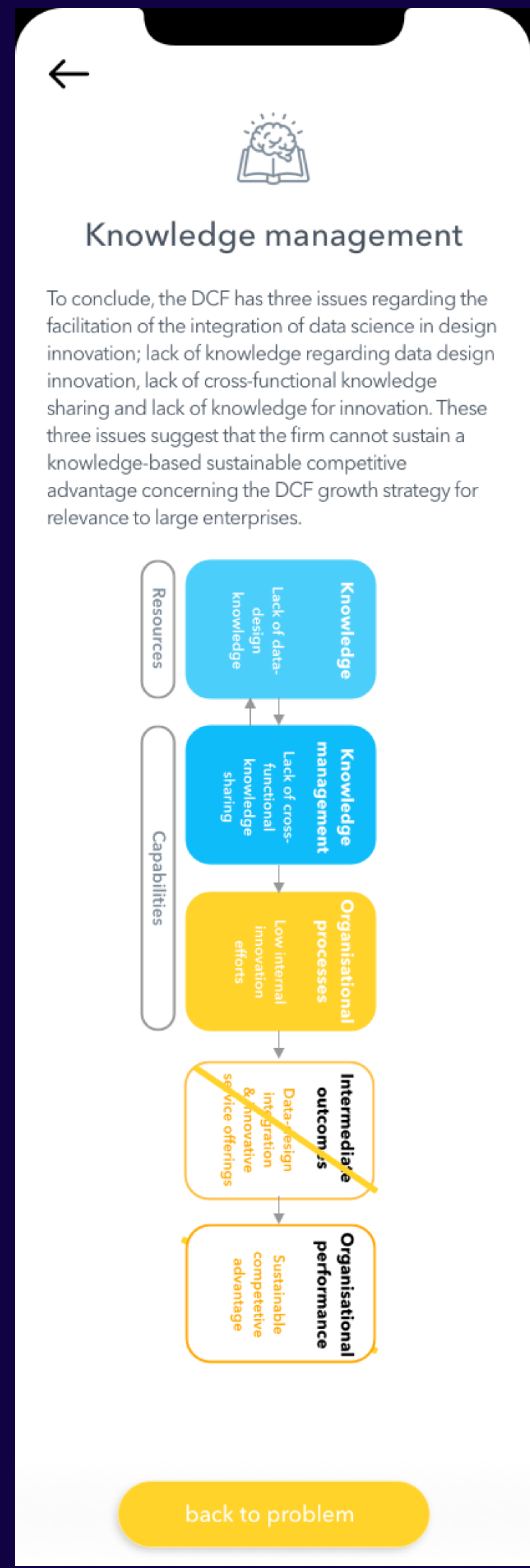

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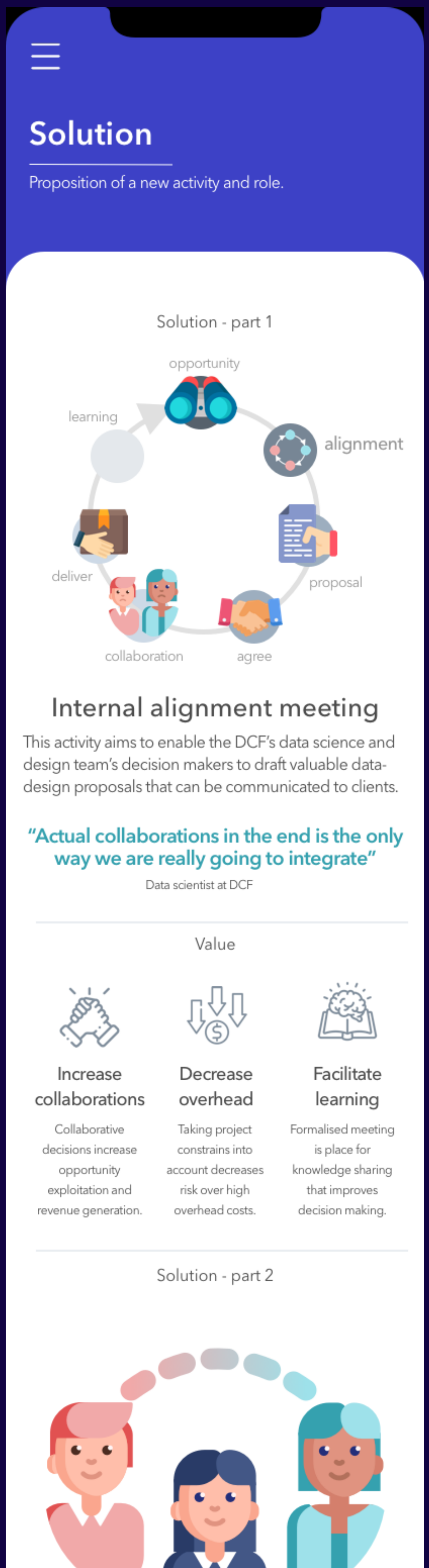
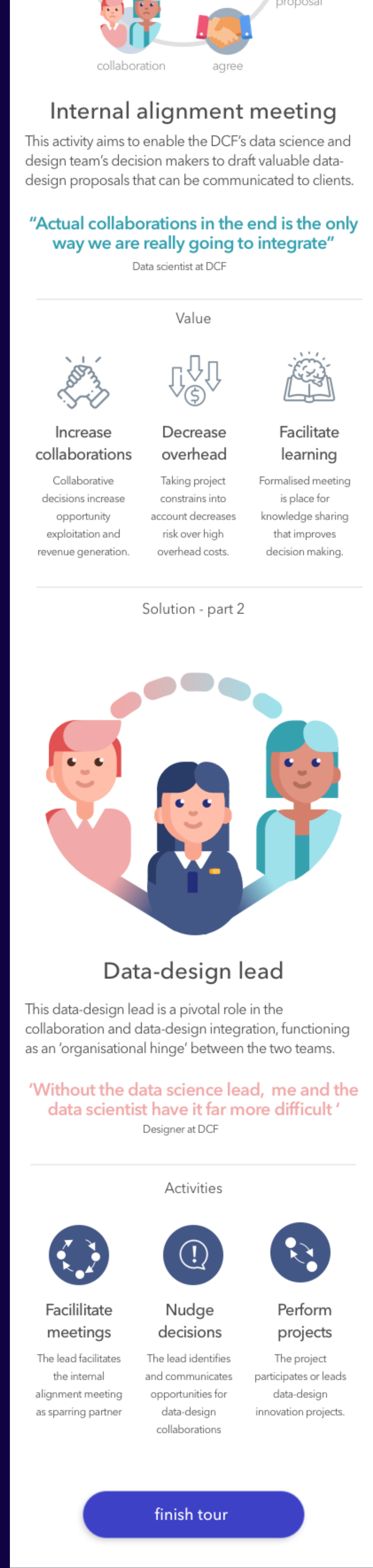
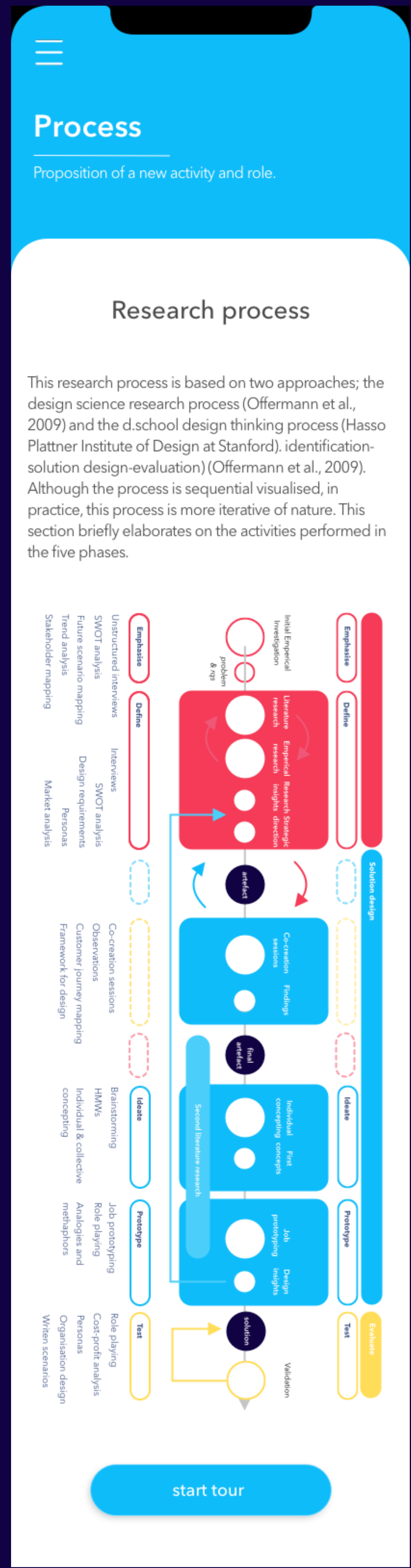
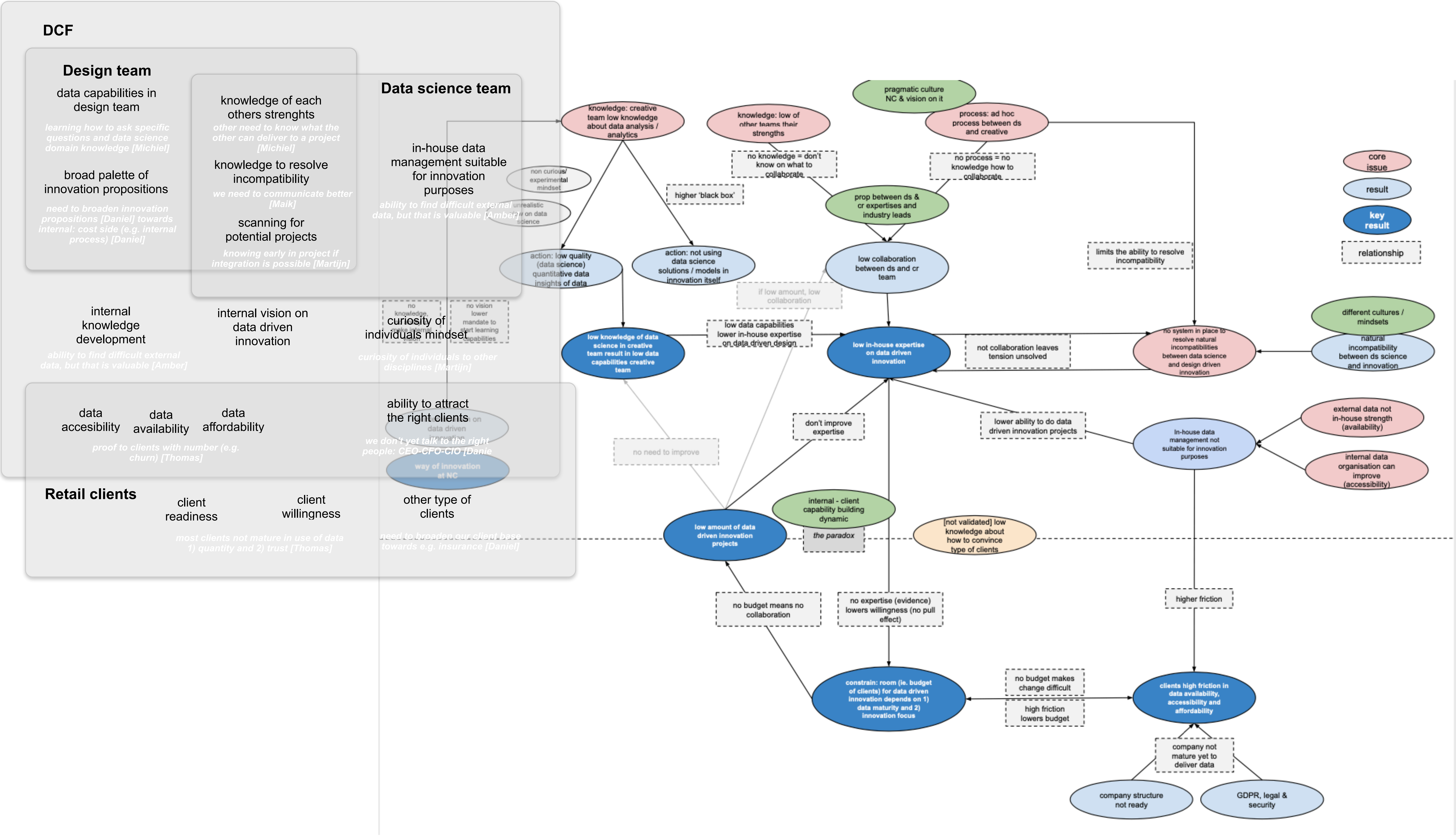






Appendix 3.4 - Conditions and dynamics

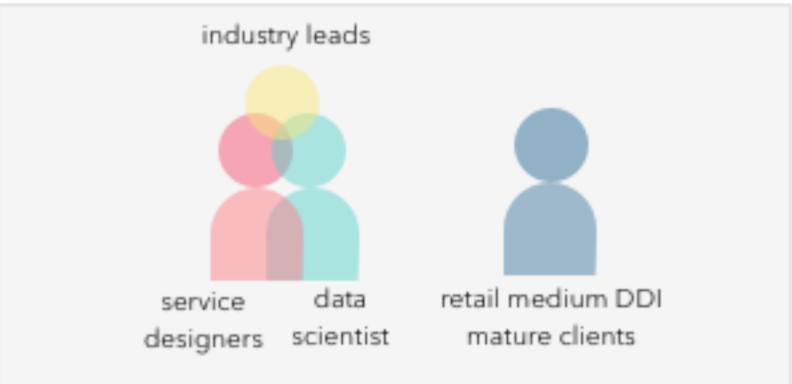
This appendix describes the emperical research performed during the research phase. This research concluded in a set of conditions for the use of data science in design-driven innovation. First these conditions are visualised. Second, the research approach is drafted.



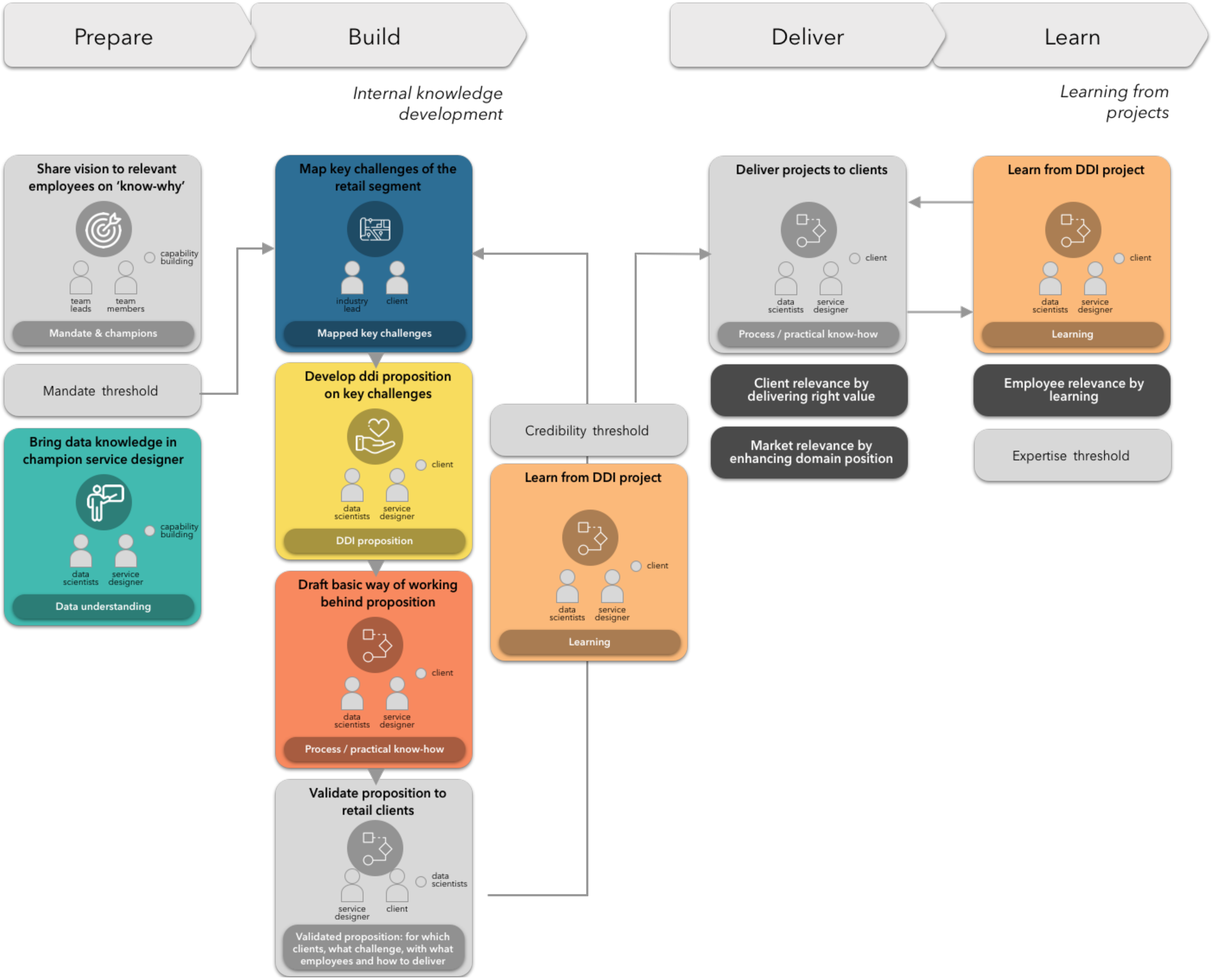
Appendix 3.5 - Artefact - framework

The primary benefit for the adoption of the DDI framework is providing a systematic approach to DCF's design team to adapt to enable their designers to use data-driven decision making in design-driven innovation projects. Although the design managers are the target group, the adoption of this framework is beneficial for the entire system of stakeholders.

Each step is based on a internal knowledge challenge. These steps can be recognised by their distinct colours. The challenges are further detailed with the addition of key activity and deliverables.



Each step is accompanied by a description of key stakeholders to include. The reasoning for including the individual stakeholders is based on conclusions from the company and client analysis.

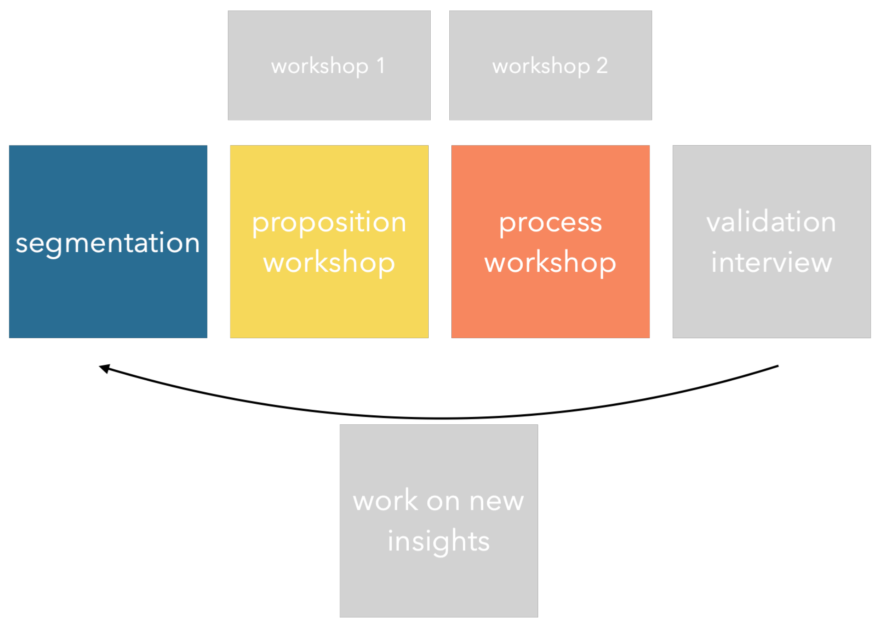


Appendix 3.6 - Artefact evaluation

This subchapter elaborates the activities performed during the first iteration. First the design process is elaborated, which resulted in the design of a sprint week. Second, the validation methodology is provided. The subchapter is concluded with the insights from the data analysis and provides the design implications.
Design

Process
Based on the build phase of the DDI framework, a sprint week (Knapp, 2016) including two co-creation sessions is designed. The design is done by individual concepting, the use of creative facilitation literature (e.g. Tassoul, 2004) and two sessions with an internal creative facilitation expert. There are three limitations taken into account in designing the sprint week; (1) available hours of employees: shape the sessions in such a way, the most time on the proposition development. (2) covid-19. This implicates two things: a low amount of participants, as online sessions are harder to have interaction.

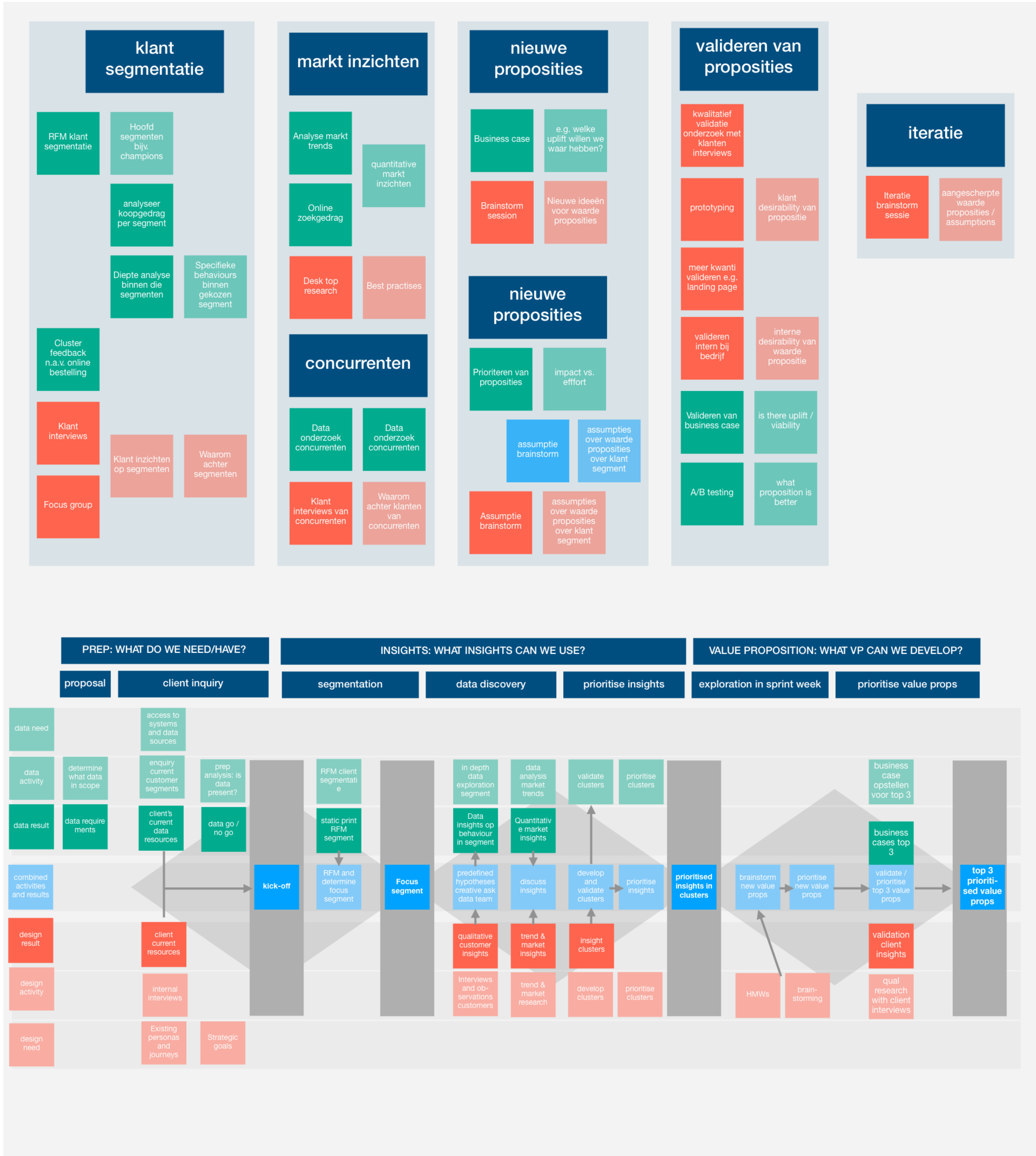
First an individual ideation session is performed to develop a first draft of the sprint weeks. The design is based on the combination between Google venture's sprint week and creative facilitation literature (e.g. Tassoul, 2004). With a sprint week you can fast-forward into the future to see your finished product and customer reactions, before making any expensive commitments. (Knapp, 2016). This resulted in two sprint week designs. (1) one actual sprint week with three sessions: one proposition ideation and prioritisation, one process building and one at the end validation with client the sprint week spread over three weeks These designs were input for two online design sessions with an internal creative facilitation expert.



Result
The design, an altered sprint week, consists of four steps with complementing workshop designs; use case development, proposition development, process development and client validation (see figure 4). The process and designs are further elaborated in Appendix 2 - Sprint week design.

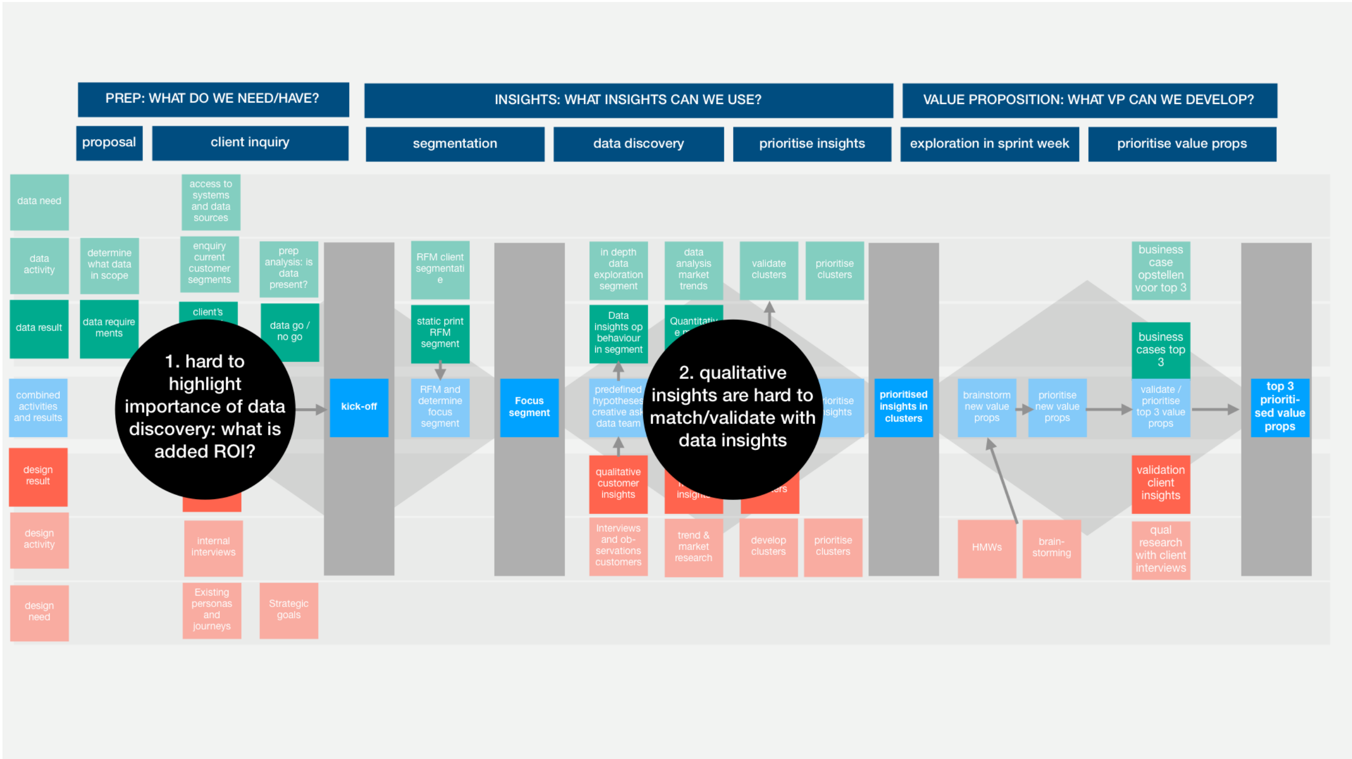
Activities
The sprint week design is performed in four steps; use case development, propositions co-creation workshops, way-of-working co-creation workshop and client demo validation. Table 1 provides an overview of the activities, the goal, the input and the participants. Between each step, the results of each activity are further concepted and used in the following workshops. In appendix 3 a more elaborate is provided on the activities performed and the individual results.

Activities performed during the sprint week
The use case is developed during a session with DCF's retail industry lead and is the following; support [company] with the development of value propositions for new digital delivery service on a least customer segmentation. The input for this session was the chosen retail client segments - blue belts and a performed desk research on retail trends concerning data-driven innovation. This use case is further detailed with the customer jobs, pains and gains on a customer value proposition canvas. The proposition workshops performed during a digital co-creation session with a data scientist and service designer of DCF. The process development is performed during a digital co-creation session with a data scientist, service designer and external expert (data-designer Phillips). In figure 1.2 the main finding of this session is visualised. During these workshops the researcher was the facilitator of the co-creation workshops. The client validation is not performed, as the process workshop resulted in two main issues that constrained both the proposition development and execution. The aim was to perform a demo-workshop interview.



Insights sprint week

Two problems during activities
The client validation is not performed, as the two workshops did not lead to the desired result; data-driven propositions and a way-of-working that could be validated with clients. During the second co-creation sessions, the participants were unable to further detail the way-of-working mainly due to two challenges; (1) it is hard to highlight the added value (ie. return on investment of clients project budget) of data science to a design project (2) it is difficult to match and validate the qualitative design insights with the quantitative data insights.



Main reason - uninformed decision making
The data findings showed a clear pattern why the participants were not able to develop a valuable value proposition. During several key moments, the participants made decisions negatively impact the ability to develop and deliver valuable client projects.

Good vs. bad decisions
By further analysis of the participants behaviour, wording and actions during the decision moments, cues were found when 'good' and 'bad' decisions were made. Bad decisions are made when participants; (1) have a lack of understanding of discipline specific terms, (2) there is a difference in language and (2) uninformed and intuitive decisions are made. Good decisions are made when (1) the decision maker has knowledge on both data and design (2) the options that both teams implicate are elaborated with examples (3) the possible decision is critically reflected (4) when the decision is iterated and improved.

Example 1 - data driven value propositions
During the use case development, DCF's retail industry lead decided to develop new digital value propositions based on client segmentation (data science activity in which the current client base is analysis on variables such as order date, budget in order to develop segments).
However, concluded from the workshops; the effort and increase in project costs of data client segmentations does not provide enough value for the development of value propositions for clients. A designer stated 'most of the time value propositions are already known by clients, they want to go to a sprint week as fast as possible, so extra discovery is not needed in their eyes'.

Example 2 - RFM segmentation as creative input
During the proposition workshop, the service designer and data scientists decided to use an RFM segmentation (typical segmentation, recency, frequency and monetary, mostly used for marketeers in order to target more specifically) as guidance for qualitative customer discovery. The service designer stated 'if we start with data; that can give direction on which people we need to interview' on which the data scientist answered 'RFM is quite high over - so that can direct design to start right?'.
However, concluded from the workshops, an RFM segmentation is not suitable for guiding design efforts, as the results only would show groups of 'digital' customers; loyalists who have high order frequency. Targeting an email could benefit from such information, a designer however not.

To conclude, the participants were not able to develop a valuable data-driven innovation proposition by performing the steps in the build phase of the DDI Framework. Prior to the way-of-working workshop, participants made uninformed, intuitive and uncritical decisions that negatively impacted the ability to deliver a (for the client) valuable collaboration.

Other relevant insights
Uninformed? Inform with collaborative value
How can we inform uninformed decisions? Concluded from the analysis, the source of information that supports decision making is the actual collaboration possibilities between the design and data team on specific client challenges where clients perceive a high ROI of adding data science. This implicates a focus on two of knowledge challenges; client challenges & internal propositions.

Invalidation proposition development as goal
From the analysis we can conclude that the knowledge needed is not 1-3 individual propositions. Rather it is stated that 'more value can be provided to DCF if knowledge is developed how the two can collaborate'.

Improve activities in steps
Proposition and knowledge development is found to be ineffective in the current order of the steps. As good decisions are made when iterative is worked, the steps are linear based. lack of iteration possibilities, decisions prior to workshops influence difficulty of performing

Invalidation WOW workshop
Way-of-working workshops not found to be influential in the success of the internal build phase; learning-on-the-job is still perceived as a more feasible and effective way of learning. In contrast, by the performance of this workshop, crucial invalidating of decisions are found, which prior were not noticed. After a case study was found, other people did have the knowledge, but were not present to share this.

It can be concluded that generating the right knowledge in the right way does not enable integration to happen between the data and design team. It is rather about the use of (or lack of) knowledge during decision making which enables (or constraints) collaboration between the design and data team. This implicates an invalidation of the DDI framework and a need to reframe the design challenge in itself.

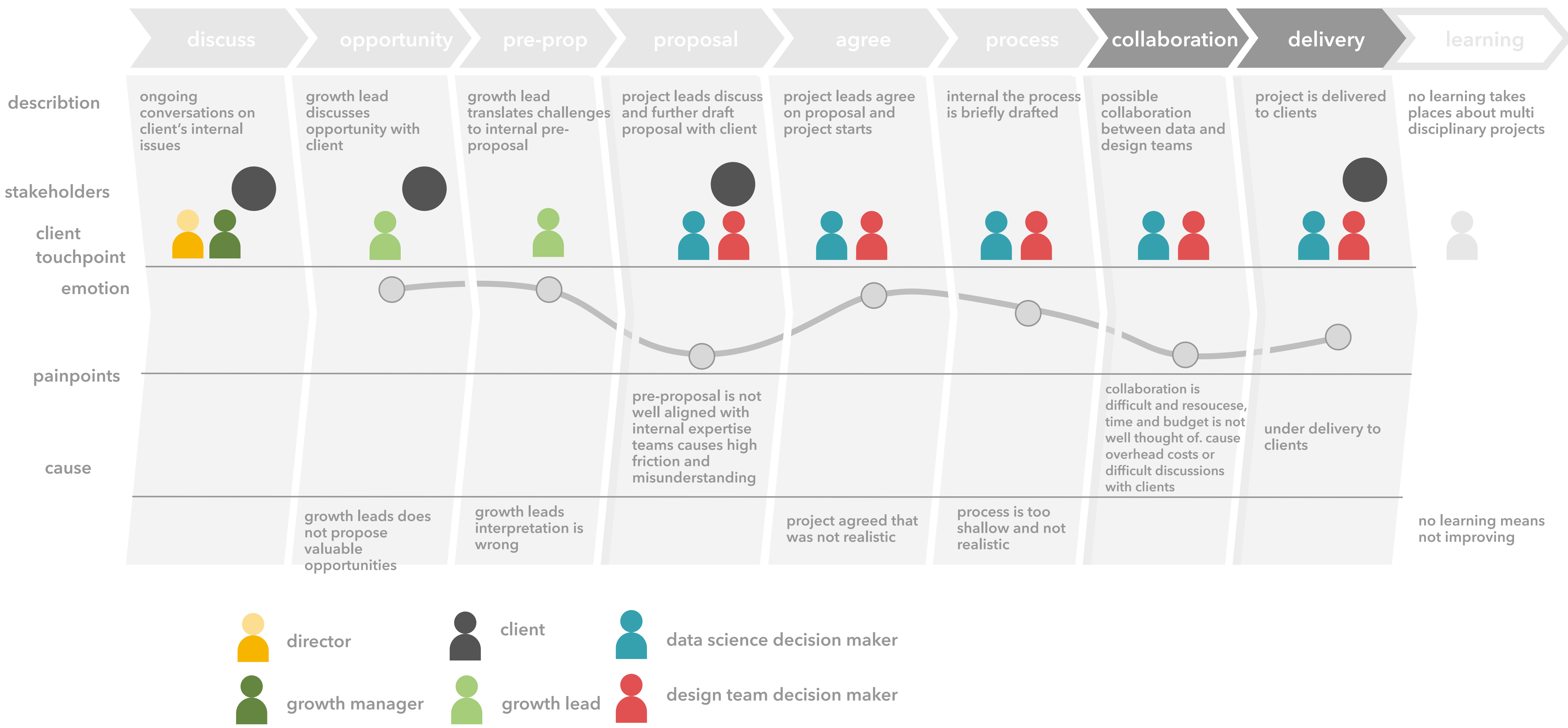
Appendix 3.7 - customer journey map session result

To further explore the DCFs decision making process and identify the largest pain points, the project journey regarding decision moments has been identified by customer journey mapping. Customer journey mapping refers to a design activity that aims to map a customers (or in this case employee's) interactions, goals, emotions and barriers throughout the use of a product (Abbing, 2010).

Below the result of that customer journey mapping sessions is visualised. The two top layers present the decisions steps decision makers in the DCF. Below each description, the stakeholders are visualised that participate in the step. Each dark dot present a touchpoint with the client. To provide an example, during the proposal step, DCF's data science and design decision makers discuss and furhter draft the project proposal with the client.

The middle layer present the emotion from each internal stakeholder. At low points the painpoint is described. Each painpoints cause(s) is further discussed below. To further clarify with the example, participants mentioned this step as 'shit in, shit out'. Meaning that in many cases the pre-proposal is not well aligned with internal expertise teams and that causes high friction and misunderstanding.

The cause for this problem has identified as the actions from the growth lead (1) growth leads does not propose valuable opportunities and (2) growth leads interpretation of the challenge is wrong.



Appendix 4.1 decision making process

Understand and determine

During the first subsystems the decision makers aim to transform the initial project brief towards a concrete challenge. The challenge should be based on a holistic understanding from a data science, design innovation and client perspective and have concrete focus. The understand phase three steps are;

review the initial briefing - The initial briefing should be analysed and critically reflected by both teams. The aim is to increase the understanding of the client's challenge from a data science, design and financial perspective. What are the client's needs and complementing challenges really? What are these from a consumer perspective? What from a data perspective?

review project resources - Often project resources are provided by clients in the initial briefing. The aim is to determine further needed critical resources and acquire knowledge about the ones that are not known. The goal is to draft a set of critical project constraints, fundamental for making better decisions.

determine challenge focus - When the challenge is reviewed from each perspective and the project constraints are drafted, a scope and focus should be given. From all different perspectives, how can we deliver the most value to the client? Are we going to deliver a data science solution or a design solution?

The analyses performed and decisions made in this phase highly determine the direction of further decisions made. However, this phase requires a complex ability to view the client's challenge from both a data science and design innovation perspective, think comparatively between those and balancing internal feasibility with the client's desirability. Further, both teams tend to be in favor of a solution that would deliver the own team's solution. Negotiating and reaching consensus are in reality common practise.

Study

Based on the determined client challenge, the data scientist and designer should study the challenge from one's own discipline's perspective in order to draft an initial team approach.

determine activity and sub deliverables - Each team needs to determine the activities the team initially envisions to solve the challenge and complementing sub deliverables. Both teams already tend to have existing service offerings that can be used during this step.

reflect on project constraints - The decision makers need to critically reflect on the envisioned approach. Does the project and the client provide the resources (data, time and budget) to perform these activities?

reflect on challenge focus - The sub deliverables need to be aligned with the client's business value. Does this deliverable contribute to the determined challenge and in what way?

A common practise in their own team's is the construction of the activities and deliverables. However, in this specific case, often the initial project proposal is either a data science or a design challenge. For this reason, resources for a certain activity are not known. These have to be asked to the client.. For both the DCFs data scientist and designer reflecting on project constraints and aligning with client's business value.

Integrate

After both the team's have determined their own approach, the two approaches have to be integrated. How do both teams' results match each other to create value? What does the data team do with a data deliverable and the other way around? This integration consists of the following seven steps;

compare both sub deliverables by illuminating assumptions - Both teams share their approaches while highlighting the argumentations. Important is using a vocabulary that allows the other discipline to understand the approach.

identify links or conflicts - After (and in practice mostly during) sharing, similarities, differences and conflicts between the approaches need to be identified. Similarities can provide instant direction for collaboration while differences can show valuable gaps for complementing. Conflicts

identify linking deliverable between disciplines - This step actually links the two sub activities and deliverables into one concrete collaborative sub deliverable. An example is segmentation, this steers the data scientist to perform a customer segmentation analysis and designers to develop personas.

construct new understanding of the challenge - Based on the chosen sub deliverable, both teams construct an understanding of the client's challenge that is aimed to be solved. This allows to specify the deliverable that is aimed to be delivered as well as the initial determined challenge.

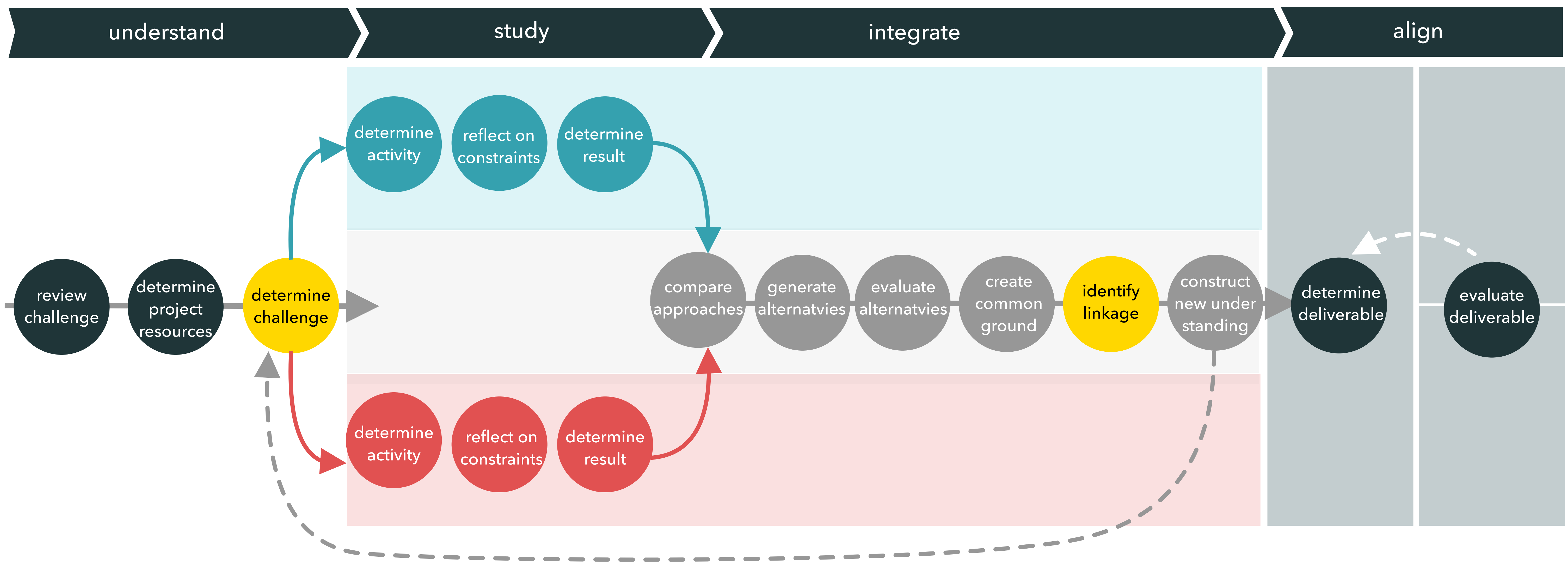
Based on analysing the decision making, the identification of linking sub deliverables is found to be both the most important decisions that needs to be made as well as the most challenging one. A linking deliverable steers both previous activities to support that subdeliverble and future activities that can build on the outcome.

Align

Last, based on the identified linking deliverable and the new understanding of the challenge that both team's aim to solve, the deliverable can be determined and evaluated.

determine deliverable - Based on the identified linking deliverable and the new understanding of the challenge that both team's aim to solve, the deliverable can be determined.

test with client value and evaluate decision effectiveness - The proposed deliverable is evaluated.



Appendix 7.2 - Thematic clustering validations

This appendix shares the results from the thematic clustering of the role-play meeting. This section shares the results of two cluster rounds. The next sections shared the final version of the codebook, the superfamilies, families, codes and quotes of participants. The names of the participants are anonomised. DS stands for Data scientist, D stands for designers and S stands for Strategist (or facilitator of the meeting). Seven themes are withdrawn, from which the latter do did not contribute to the validation of the job holder but rather the meeting itself of the difference between the teams. The last section shares the transcribts of the audio recordings.

1. Ability/power to make well argumented choices (convincing) from working experience that unite the teams and steer in the right direction
    a. Make choices
        i. drafting a good starting point ('kick-starter') on which both teams can further build: ik heb een post-it in jouw bol geplakt met 'proceskosten prioritering'; als jij van M een service blueprint hebt gekregen en je snapt welke processtappen eruit komen, dan kan je volgens mij gaan uitzoeken, goh hoeveel kost deze stap en waar kan ik een geautomatiseerde data oplossing
        ii. drafting an approach & way-of-working: idealiter wil je gaan pingpongen tussen data en design, en zo werkt het praktisch ook
    b. Has decision power
        i. has previous experience working with both teams
    c. Ability to spot common deliverables that unite the teams
        i. stating the touchpoints between the two teams
2. Ability to get both teams on the same wavelength by communicating in both languages.
    a. Ability to communication with both parties and translate to each other
        i. relation therapy: relatietherapie gedaan
        ii. can speak both languages
        iii. know how to draft hypothesis and translate those to both teams
3. Ability to make decision alternatives more clear (issue trees, examples and analogies)
    a. Make choices more clear
        i. drafting issue tree to make decisions clear
    b. Providing examples & analogies
        i. providing examples: guided the participants to make decisions and make action more clear
        ii. using analogies to make things more clearly '[D] huis voor de klant, en ik vind niet dat heipalen een waarde hebben, dat betekent niet dat die heipalen geen waarde hebben, ook al is het niet iets dat zichtbaar is aan het eind van het project'
4. Coach and support decision makers with suggestions, coaching and challenging.
    a. Providing suggestions (supporting)
        i. providing suggestions
    b. Advise on choices (coaching)
        i. advising on best action to take
        ii. can answer questions asked of what action to take
    c. Ability to challenge current way of thinking
        i. get people out of their current way of thinking (out of tunnel visions)
5. Ability to put client & business goals central and reflect critically on possibilities
    a. put client business perspective & business goals central in decisions: '10% kosten besparen, ongelofelijke impact op een bedrijfsresultaat!
    b. knows both processes and activities

Results from final cluster activity - 5 abilities why the facilitating lead had a positive influence on the decision making of the two teams.

1. Ability to communication with both parties and translate to each other
    a. relation therapy: relatietherapie gedaan
    b. can speak both languages
    c. know how to draft hypothesis and translate those to both teams
2. Make choices more clear
    a. drafting issue tree to make decisions clear
3. Providing examples & analogies
    a. providing examples: guided the participants to make decisions and make action more clear
    b. using analogies to make things more clear '[D] huis voor de klant, en ik vind niet dat heipalen een waarde hebben, dat betekent niet dat die heipalen geen waarde hebben, ook al is het niet iets dat zichtbaar is aan het eind van het project'
4. Providing suggestions (supporting)
    a. providing suggestions
5. Advise on choices (coaching)
    a. advising on best action to take
    b. can answer questions asked of what action to take
    c. stating the touchpoints between the two teams
6. Make choices
    a. drafting a good starting point ('kick-starter') on which both teams can further build: ik heb een post-it in jouw bol geplakt met 'proceskosten prioritering'; als jij van M een service blueprint hebt gekregen en je snapt welke processtappen eruit komen, dan kan je volgens mij gaan uitzoeken, goh hoeveel kost deze stap en waar kan ik een geautomatiseerde data oplossing
    b. drafting an approach & way-of-working: idealiter wil je gaan pingpongen tussen data en design, en zo werkt het praktisch ook
7. Has decision power
    a. has previous experience working with both teams
8. Ability to challenge
    a. get people out of their current way of thinking (out of tunnel visions)
9. Put client & business goals central
    a. put client business perspective & business goals central in decisions: '10% kosten besparen, ongelofelijke impact op een bedrijfsresultaat!

Results from preliminary cluster activity - 9 abilities why the facilitating lead had a positive influence on the decision making of the two teams.

Appendix 7.1 - Business case

This appendix shares the business case. Viability is highly valued by management, as commercial benefits are still priority in the organisation. Any change has to be seen as a valuable investment, something that has high return.

Requirements
Determine costs of solution
Determine main financial benefit; short & long term
Calculate business case
The business model key costs structure is salary
The BM key revenue stream is billable hours

Options
Option 1: including wow activity with strategist before proposal
Option 2: wow with strategist after proposal activity
Option 3: wow during collaboration

Proposed: including a critical (small) wow activity before delivering a proposal. The earlier in the process the project dynamics are determined, the higher the potential for collaboration value to deliver. The goal is not to develop an entire way-of-working, as project dynamics tend to change during the project. However, calculating the time, costs, order of activities.

Key metrics
Increase in data-design project sales; easy metric to measure

Sub metrics
Increase in number of opportunities spotted
Increase in client communications
Increase in effectiveness data-design proposals
Decrease in time between opportunity and client communication

Soft metric: increase in learning by the teams; difficult metric to measure
decrease in hours needed for support
increase in opportunities individually spotted; easy metric to measure. This can be implemented in the system as reflection activity and even be compared to bonus for extra nudging.

Conclusion
Conclusions; the increase in salary costs, with a minimum amount of effort leads to high increase in project sales.

	What	Number	Argumentation
Cost of lead and complementing activities	Amount of hours per month	26	see below
	Salary per month	€ 8.000	assumed salary new role - from strategy lead
	Salary cost lead	€ 1.300	
	Salary cost data scientist	€ 1.300	salary senior data scientist - from strategy lead
	including billability loss	€ 3.250	billability of 50%
Revenue generated by new lead	Amount of proposals	20	provided by strategy lead - based on company data
	Hours per month	26	based on observations and emperical research - calculated with 20 proposals
	Conversion ratio of	0,1	provided by strategy lead - based on conversion rates
	Success rate	2	
	Revenue generated by data scientist per month	€ 14.000,00	internal research
	Revenue from data components	€ 28.000,00	
	Extra revenue generated	€ 24.750,00	

Results from final cluster activity - 5 abilities why the facilitating lead had a positive influence on the decision making of the two teams.

Appendix 7.2 - Thematic clustering validations

Thema	Cluster	Code	Quote	
Discussion starter	Challenge insights	keuze gemaakt door designer	maar laten we die NPS dan pakken; kijken met welke onderdelen scoren we dan een NPS	D
	Challenge insights	correctie strateeg vanuit expertise	[M] je hebt de blueprint wel nodig, want als je naar implementatie gaat, dan moet je dit wel weten	D
	Challenge insights	twijfel in aanpak	[C] voor mijn gevoel hinken we nu op twee gedachtes, ene zijds heel erg in die NPS en anderzijds heel erg weggestuurd, om kosten reductie uit te voeren voor AEGON	DS
	Challenge insights	waarde van data	het feit dat het voor het data team om iets direct te meten, wil niet zeggen dat je er niet indirect aan kan bijdragen,	S
	Challenge insights	niet hoeven meten	het feit dat het voor het data team om iets direct te meten, wil niet zeggen dat je er niet indirect aan kan bijdragen,	S
	Challenge insights	data drijft project	niet uiteindelijk weten hoe je het hele project optimaliseren, maar te drijven	S
	Challenge insights	effort vs. impact	[D] effort en impact niet door elkaar halen	S
	Coaching	valideren, neerzetten argumenten van data voor design	design vraagt aan data; leuk dat je met de kostenbesparing bezig bent, maar we willen wel graag weten wat 'is nou de doelgroep waar de meeste NPS verbetering te halen valt; hoe groot te groep, hoe laag de NPS, wat voor schadegevallen'	S
	Coaching	valideren, neerzetten argumenten van data voor design	profiel analyse gaan vragen aan het data team	S
	Advice	uit tunnel halen	dan zitten we al heel erg in de oplossingsrichting	S
	Advice	mogelijkheden voorleggen	[D] er zijn een aantal manier hoe je de kubus door kan snijden; -klantsegmentatie -activiteiten (schade afhankelijk - schade afhankelijkheid	S
	Suggestion	activiteit bepalen voor data scientist	[D] ik heb een post-it in jouw bol geplakt met 'proceskosten prioritering'; als jij van M een service blueprint hebt gekregen en je snapt welke processtappen eruit komen, dan kan je volgens mij gaan uitzoeken, goh hoeveel kost deze stap en waar kan ik een geautomatiseerde data oplossing tegen aan plakken om dit kost efficiënter te doen	S
	Suggestion	actie uitzetten	wat ik zou doen; we hebben met z'n allen door de lens gekeken, dit is wat we nodig hebben, nu kiezen we de top 5 duurste activiteiten uit in ons operationeel process, kijken met data & creative brainstormen hoe we dat goedkoper kunnen maken	S
	Suggestion	argumenterende rol van data	hoe data kan bijdragen aan een strategy of aan een design vraagstuk (zonder naar een deliverable toe te werken hoe ze dat wel doen, voorspelling models, rfm model) maar door kleine subvragen te beantwoorden die als een soort van proxy werken voor wat andere teams aan het doen zijn	S
	Answer questions	vraag voor een keuze aan strateeg	[C] D aan jou nu ook de vraag; jij wilt een prioritering hebben van is het eigen next best action? voor welke klant doen we wat? CLV? kosten van een bepaalde schade?	DS
CHoose	Approach / way-of-working geven	Data onderbouwen keuzes design	design; data moet verrijken en onderbouwen van de keuzes die gemaakt worden	S
	Approach / way-of-working geven	Design input leveren voor data	data; design moet helpen met input leveren (service blueprint om data helpen prioriteren waar nieuwe data solution opgeleverd gaat worden)	S
	Approach / way-of-working geven	way-of-working voorbeeld	idealiter wil je gaan pingpongen tussen data en design, en zo werkt het praktisch ook	S
	Approach / way-of-working geven	data faciliterende rol aan design	(om het doel van de journey te valideren)	S
	Approach / way-of-working geven	data faciliterende rol aan design	faciliterende rol van data	S
	Approach / way-of-working geven	data validerende rol	komt dan dat gedrag overeen met wat ik in me ideation heb gedefinieerd.	DS
	Ability to spot toychpoint	Data prioriteren van design	prioriteit voor klantsegment	S
	Ability to spot touchpoint	touchpoint neerzetten tussen twee teams	wat ik zou doen; we hebben met z'n allen door de lens gekeken, dit is wat we nodig hebben, nu kiezen we de top 5 duurste activiteiten uit in ons operationeel process, kijken met data & creative brainstormen hoe we dat goedkoper kunnen maken	S
	Startpunt bepalen	richting adviseren	ik zou die beide hand in hand houden en als je dat nou iteratief doet, dit design komt met een pijnpunt in de customer journey en data vertellen hoe zwaar dat pijnpunt is, iteratief op zoek naar oplossing	S
	Startpunt bepalen	beginpunt neergezet	[D] als je bij design begint; en design zou een service blueprint kunnen opleveren	S
Align teams	speak both languages	data heel concreet	[D] het normale data process, met validatie van data qualiteit, messcherpe afbakeningen KPI's	S
	speak both languages	Verschil in granulariteit	andere granulariteit	S
	speak both languages	Andere golflengte	maar ook echt andere golflengte	S
	speak both languages	faciliterende rol afnemen	[D] ik zou hopen dat dat over tijd niet meer nodig is (de faciliterende rol)	S
	speak both languages	1 team project lead	**1 faciliterend maken van de ander: niet stiekem proberen om allebei een deliverable op te leveren**	S
	speak both languages	design trainen in hypothese	waar het design team ingetrained kan worden, breng nou eens scherp onder woorden wat de hypothese is,	S
	speak both languages	data trainen in creatief valideren	dan mag het data team uitgedaagd worden; hoe kan je bij gebrekkige data, toch een bepaalde vooronderstelling kan vinden	S
	translate	rol strategie als brug	een van de maturity modellen; die heb ik toen bij design neergelegd, jongens moet je kijken; iemand moet op ze minst 1 keer terugkomen, dan wordt die heel veel geld waard	S
	translate	rol strategie als brug	we zijn gewend uit een strategy project om aan het begin hypotheses te formuleren 'en toen ook vrij makkelijk een bakje met hypothesis neergelegd, zoek zelf maar welke data je nodig hebt en zoek het maar uit'	S
	translate	relatie therapie	relatie therapie gedaan,	S
	translate	andere bril tussen teams	; wordt echt fundamenteel andere bril opgezet tijdens projecten	S
	translate	fundamentele verschillen	; wordt echt fundamenteel andere bril opgezet tijdens projecten	S

Final codebook part 1 - Themes, clusters, codes and quotes from anonimes participants.

Business central	busienss perspective	business goal voorop	'10% kosten besparen, ongelofelijke impact op een bedrijfsresultaat!	S
	busienss perspective	refereer naar klant	we doen het echt voor AEGON he	S
	busienss perspective	business case	kans dat iemand terugkomt = x% winst die je maakt na 3e bezoek is y€ - dus x*y = de waarde van het terug laten komen van de klant	S
	busienss perspective	industrie inzicht	sector inzicht van strateeg schade afhandelingskosten grote kostenpost in deze sector;	S
	busienss perspective	klantperspectief belang neerzetten	maar voor welke klanten doen we dit dan?	D
	busienss perspective	klant keuze	[M] is wel een belangrijke keuze voor die to be journey: bij huidige journey maakt het nog niet uit, maar als je naar oplossingen gaan kijken, een nieuwe journey natuurlijk wel	D
	critically on constraints	klantperspectief	maar ook vanuit een klantperspectief natuurlijk	S
	know both sides	informeren van participants	kleine kanttekening; mensen die de telefoon opnemen zijn hoger opgeleid, en kosten een belletje gauw 35 euro	S
	know both sides	Concretiseren business waarde	[D] iets formeler antwoord geven; waarde is op zijn minst twee ledig, dus betere NPS en/of lagere kosten, alle activiteiten die we hier nu doen moeten of direct tot een betere NPS/kostenreductie leiden of noodzakelijk zijn voor een vervolg activiteit	S
Clarify alternatives	Example	voorbeeld van strateeg	Citizen M; 1+1=3 (design en data, waar strategy het aan elkaar kletts); samen meer dan de som per delen	S
	Example	herkenning naar case	ik herken Balier hier heel erg goed in terug; daar ging het om bestellen van part	D
	Example	1+1=3	samen meer dan de som per delen	S
	Example	data subvragen beantwoorden	data heeft allerlei subvragen beantwoord, die alles bij elkaar argumenten waren in een groter verhaal	S
	Example	keuze herhaling strateeg	[D] maar kostenreductie is even geparkeerd.	S
	Example	voorbeeld geven	wat lekker werkt; citizen M hebben we toen ook een wat vage klant opdracht naar wat hardere KPI waar een data team ook wat mee kan, dus dat zou in dit geval zijn, hoe kan AEGON haar klanten service OPEX minimaliseren en haar klant NPS maximaliseren?	S
	Issue tree	Issue tree opzetten	kan helpen met een design team aan te zetten; hoe kunnen we nou echt een betere customer journey gaan opzetten / en een data team aanzetten; waar zitten de OPEX reductie kansen	S
	Issue tree	issue tree verduidelijken	in mijn hoofd had ik hem al uit elkaar getrokken; waar de meeste kosten reductie kan realiseren / en welke klant je de journey voordoet, hoeft niet noodzakelijk dezelfde doelgroep te zijn	S
	Issue tree	issue tree verduidelijken	[D] boompje en je hebt tweedeling gemaakt, en je durft twee groepen parallel aan elkaar te gaan	S
	Anology	analogie gebruikt	idealiter wil je gaan pingpongen tussen data en design, en zo werkt het praktisch ook	S
	Anology	analogie gebruiken voor verduideiljking	[D] huis voor de klant, en ik vind niet dat heipalen een waarde hebben, dat betekent niet dat die heipalen geen waarde hebben, ook al is het niet iets dat zichtbaar is aan het eind van het project	S
Value of solution	waarde workshop	gebeurt weinig	] ja ja, dat gebeurd nu echt te weinig	D
	waarde strateeg	moeilijker	ik denk dat; als cornelis en ik met elkaar hadden gezeten zonder daniel erbij, dat het veel moeilijker was geweest	D
	waarde workshop	interresant	ik denk dat dit ook wel een interessant ding blootlegt waarom	D
	waarde workshop	waarde van groep	heel waardevol om zo met dit groepje te gaan zitten	DS
	waarde workshop	waarde van discussie	ik vond de discussie erg waardevol	DS
	waarde workshop	discussie nodig	je ziet de manier waarop deze discussie gaat, dat we ook nog veel discussie nodig hebben	D
	meerwaarde samenwerking	1+1=3	1+1=3	S
	waarde samenwerking	leuk zijn	het moet ook gewoon leuk zijn	S
	waarde samenwerking	wil samenwerking	'ik wil gewoon met cornelis samenwerking, ik heb nog nooit een project	D
	waarde samenwerking	doen	eigenlijk heb ik bij dit project, laten we dit gewoon gaan doen	DS
	waarde samenwerking	te weinig doen	en veel te weinig doen met elkaar	D
	commerciele waarde samenwerking	minder mensen nodig	met minder mensen een project doen	S
	commerciele waarde samenwerking	meer soorten projecten	meer soorten projecten doen	S
Difference between teams	onbegrip data science voor design	onbekend terrein	nu begeef ik me op onbekend terrein	DS
	onbegrip data science voor design	disconnect	disconnect	DS
	onbegrip data science voor design	fuzzyness design	dat zijn soms hele fuzzy dingen, die totaal geen concreetheid in zich hebben, en dat ontdek je juist met design	D
	onbegrip data science voor design	waarde aantonene data science	[C] waarde aantonen heel lastig voor data als het fuzzy is,	DS
	onbegrip data science voor design	uitdaging voor data science	is ook duidelijke uitdaging voor het data team	DS
	onbegrip data science voor design	vastlopen	**Dus vandaar dat ik hier op vastloop, als we op NPS gaan zitten te focussen, vanuit data oogpunt hebben we een probleem om aan te tonen wat het doet.**	DS
	verschil tussen teams	uitdaging	ook een uitdaging is om elkaar te blijven vinden C	D
	verschil tussen teams	andere KPI	**NPS is bij ons meer een secundaire KPI,**	DS
	verschil tussen teams	challengen van elkaar	om ons daarop te challenges,	DS
	verschil tussen teams	concreet	**ik merk aan mezelf en dat het data team heel erg kan gaan denken, we gaan gewoon iets heels concreet, iets heel kleins oplossen, waarvan we de waarde ook heel erg concreet gaan proberen te maken, zo proberen te gaan bewijzen en dat is dan heel de casus.**	DS
	verschil tussen teams	breder	**Nu wordt het een stuk breder getrokken**	DS
	verschil tussen teams	afgeleerd	**wat wij eigenlijk zijn afgeleerd**	DS
	verschil tussen teams	data perspectief	**niet een voldoende KPI vanuit een data perspectief,**	DS
	verschil tussen teams	gedwongen	**altijd gedwongen in het vormpje**	
	onzekerheid / faalkans vanuit data science	grip	**daardoor verlies je namelijk grip**	DS
	onzekerheid / faalkans vanuit data science	moeilijke metrics	**NPS een heel moeilijke metric om op te sturen,**	DS
	onzekerheid / faalkans vanuit data science	faalkans	**kans dat dit gaat falen groter dan dat het gaat lukken**	DS
	onzekerheid / faalkans vanuit data science	dichtimmeren van oplossing	**Sinds we dit hebben ingevoerd, zijn het gelijke aantal schade gevallen, maar 40% minder via de telefoon (+NPS is niet significant gedaald) en dan heb je hem dicht getimmerd.**	DS
	onzekerheid / faalkans vanuit data science	bewijzen	**Sinds we dit hebben ingevoerd, zijn het gelijke aantal schade gevallen, maar 40% minder via de telefoon (+NPS is niet significant gedaald) en dan heb je hem dicht getimmerd.**	DS
	onzekerheid / faalkans vanuit data science	waarde aantonen	**hoe kan je waarde aantonen.**	DS

Final codebook part 2 - Themes, clusters, codes and quotes from anonimes participants.

Appendix 7.2 - Thematic clustering validations

Transcript workshop

Author: A
Data scientist: M
Designer: C
Strategist: D

Introductie presentatie Nick
Fijn dat jullie allemaal aanwezig kunnen zijn vandaag

Kort vertellen over het project, 5 minuten
Waar gaat het project over; ..
Twee problemen
(1) missen kansen om data te integreren
(2) samenwerking die niet volledig potentieel te halen

[D] twee vragen tijdens introductie
(1) aangenomen hoe dan ook waar; dat Newcraft zich moet aanpassen?
(2) zit er een bias op design naar data? Antwoord: geen bias, express gescoped beslissing gemaakt op met design oogpunt te kijken

[M] opmerking over framework
" hier kan je bovenin of onderin instappen, dus haal je die bias ook weg natuurlijk

[M]
" misschien een voorbeeld erin plakken gaat wel helpen om de templates beter te begrijpen, beetje richting geven

[C]
'hoe diepen moeten we erin gaan? wat komt er anders te staan, hoe denk jij michiel?
[M]
- 'ik zou persona als een soort design deliverable zien, maar die zie ik nu niet terug komen'
- 'dat is waarom ik geïnteresseerd ben in die klantsegmenten'
- 'zodat ik weet welke klanten ik moet interviewen, en die vat ik samen in een persona
- dat je de grootte gekwantificeerd maakt

[A]
Nu de rolverdeling in de oefeningen, mijn rol is meer faciliterend voor de structuur van de oefeningen en de tijd
Vragen over hoe dingen kunnen samenkomen etc. is de rol van Daniel
Daniel zit hierbij om nu de connectie te maken
Dus nu voor mij de tijd om stil te zijn

[D]
ik zat nog te zoeken wat mijn rol precies is, is mijn rol mee te gaan denken wat de activiteiten zijn, of dat ik alleen maar commentaar moet geven op de input van beide

[A]
combinatie tussen de twee. jouw rol is faciliterend; semi-bedenken hoe het moet, en de vrijheid te geven om hun het zelf te leren deze stappen te zetten

[D]
help ik nu actief mee met het invullen van de oefening,

[A]
- faciliterende rol
- eerste instantie CM zelf de leiding te nemen
- en dan iets later instappen

[D]
ik ga me best doen

[A]
nu ga ik stil zijn en jullie aan de slag te laten gaan

[M]
business goal, moeten we natuurlijk naar de use case kijken

[D]
we doen het echt voor AEGON he
[C]
oja die AEGON case ja; het reduceren van telefoon door digital services voorop te stellen
want dan is de case die hier achter zit; elk telefoontje kost 5 euro, dat is gewoon duur, en dus je moet zoveel mogelijk dat zien te vermijden
[D]
kleine kanttekening; mensen die de telefoon opnemen zijn hoger opgeleid, en kosten een belletje gauw 35 euro
[C]
ja precies, check

[OB]
the participants were first busy with making the business case their own, before filling in the template

[C]
goal en need liggen vrij ver uit elkaar; the goal is heel specifiek, en de needs zijn wat breder
[M]
maar ook vanuit een klantperspectief natuurlijk
[C]
gaan we nu oplossingen bedenken, die ervoor zorgt beter te voorspellen wat iemands behoefte is voordat ze op de website komen?
[D]
dan zitten we al heel erg in de oplossingsrichting
[C]
of gaan we breder zitten om afwegingen te maken, data analyse, voordat we uberhaupt op het punt komen om welke oplossen we ze dan wel of niet voorstellen

Issue tree
[D]
wat lekker werkt; citizen M hebben we toen ook een wat vage klant opdracht naar wat hardere KPI waar een data team ook wat mee kan, dus dat zou in dit geval zijn, hoe kan AEGON haar klanten service OPEX minimaliseren en haar klant NPS maximaliseren?
- kan helpen met een design team aan te zetten; hoe kunnen we nou echt een betere customer journey gaan opzetten
- en een data team aanzetten; waar zitten de OPEX reductie kansen
- zien jullie ook zo?
[M]
OPEX minimalisatie is hele concrete waar cornelis helemaal los gaan gaan
ook vanuit design te begrijpen; hoe werkt dat dan? een process bevoorbeeld

[D]
ik zou die beide hand in hand houden en als je dat nou iteratief doet, dit design komt met een pijnpunt in de customer journey en data vertellen hoe zwaar dat pijnpunt is, iteratief op zoek naar oplossing
[M]
ik herken Balier hier heel erg goed in terug; daar ging het om bestellen van part
inefficient process aan de achterkant zit; process in elkaar, order etc. wat kan je hier mee besparen, 1 FTE op weekbasis
en aan de andere kant; hoe kunnen we het bestellen nou gemakkelijker maken, interviews op los laten, zodat we aan de achterkant ook gingen faciliteren

Sectorspecifieke informatie om op weg te helpen
[D]
sector inzicht van strateeg schade afhandelingskosten grote kostenpost in deze sector;

Startpunt door strategist
[D] als je bij design begint; en design zou een service blueprint kunnen opleveren
- wat zijn de klant stappen
- heeft design startpunt; hoe kunnen we die beter gaan maken
- heeft data startpunt; wat zijn de meest kostenefficiënte stappen
[M] um ja?

Transcribt from audio recordings validation workshop - part 1

[M] designer kan vanuit hier alle activiteiten invullen die nodig zijn om deze service blueprint te maken; is een deliverable (vanuit daar needs en activiteiten bedenken)

[D] ik heb een post-it in jouw bol geplakt met 'proceskosten prioritering'; als jij van M een service blueprint hebt gekregen en je snapt welke processtappen eruit komen, dan kan je volgens mij gaan uitzoeken, goh hoeveel kost deze stap en waar kan ik een geautomatiseerde data oplossing tegen aan plakken om dit kost efficiënter te doen
[A] ziet cornelis dat ook zo?
[C] ik was nog even de needs aan het invullen

[D] volgens mij ben jij nu bezig met het invullen van de Needs voor zo'n prioritisatie, en volgens mij is M met het invullen van de activiteiten voor die service blueprint, dus volgens mij gaat het nu wel lekker zo

[C] ik ben nu gewoon aan het kijken wat we überhaupt nodig hebben om een analyse uit te kunnen voeren, ik volg jou een beetje N om wat shit erin te gooien en dan zien we wel later hoe en wat

[A] vraag ik tegelijkertijd aan M; wat is de business waarde van de service blueprint? wat levert dat op voor het bedrijf
[M] … het brengt werelden bij elkaar uiteindelijk, je mapt de voorkant (hoe wil iemand door een process heen gaan) en die komt samen met de achterkant
[D] iets formeler antwoord geven; waarde is op zijn minst twee ledig, dus betere NPS en/of lagere kosten, alle activiteiten die we hier nu doen moeten of direct tot een betere NPS/kostenreductie leiden of noodzakelijk zijn voor een vervolg activiteit
- betere NPS gaan we alleen maar krijgen met een betere journey
- betere journey gaan we alleen maar krijgen als we de huidige journey in kaart hebben gebracht

[D] huis voor de klant, en ik vind niet dat heipalen een waarde hebben, dat betekent niet dat die heipalen geen waarde hebben, ook al is het niet iets dat zichtbaar is aan het eind van het project

[C]; ik klop hier nu gewoon even onze standaard aanpak eruit, die we hebben vanuit need en activity. data need is wat het is

[A] we hebben nu de blueprint, wat dan?
[C] D aan jou nu ook de vraag; jij wilt een prioritering hebben van is het eigen next best action? voor welke klant doen we wat? CLV? kosten van een bepaalde schade?
[D] er zijn een aantal manier hoe je de kubus door kan snijden; -klantsegmentatie -activiteiten (schade afhankelijk - schade afhankelijkheid
- wat ik zou doen; we hebben met z'n allen door de lens gekeken, dit is wat we nodig hebben, nu kiezen we de top 5 duurste activiteiten uit in ons operationeel process, kijken met data & creative brainstormen hoe we dat goedkoper kunnen maken

[M]
maar voor welke klanten doen we dit dan?
- we gaan ons op een bepaald type gebruiker typen
- we hadden al een gevoel, dat we ons gaan richten op de business traveller en niet de leisure
- hele hoge scheiding geweest; gaf voor de journey op dat moment al heel veel richting

[D]
in mijn hoofd had ik hem al uit elkaar getrokken; waar de meeste kosten reductie kan realiseren / en welke klant je de journey voordoet, hoeft niet noodzakelijk dezelfde doelgroep te zijn

zijn ook twee levende projecten; twee levende bedrijfsdoelstellingen

[M] uhmmmm..

[D] terechte vraag; kostenreductie, chatbot voor huis tuin en keuken klanten / NPS verhogen zit bij meer complexe klanten die niet goed geholpen worden die gaan klagen op facebook
- naar de klant; ben je het dan eens om dit naast elkaar te gaan oplossen? kan antwoord ja / nee zijn
- is een hele belangrijke keuze dan, dat je dan misschien wel naast elkaar heen gaat werken in twee verschillende projecten
[M] is wel een belangrijke keuze voor die to be journey: bij huidige journey maakt het nog niet uit, maar als je naar oplossingen gaan kijken, een nieuwe journey natuurlijk wel
[D] boompje en je hebt tweedeling gemaakt, en je durft twee groepen parallel aan elkaar te gaan
- design vraagt aan data; leuk dat je met de kostenbesparing bezig bent, maar we willen wel graag weten wat 'is nou de doelgroep waar de meeste NPS verbetering te halen valt; hoe groot te groep, hoe laag de NPS, wat voor schadegevallen'

[OB] data scientist al lange tijd erg stil

[D]
profiel analyse gaan vragen aan het data team
[C]
uiteindelijk komt dat weer terug op het punt waar we mee begonnen; 'kosten-reductie prioritering, klant profiel analyse was eruit komt; segmenten, activiteiten, hoe groot'

[D]
idealiter wil je gaan pingpongen tussen data en design, en zo werkt het praktisch ook
wat dit wat lastiger maakt; je hebt twee doelstellingen (NPS/kostenreductie) en daarom ook twee pingpong stromen krijgt

[D]
NPS ligt dichter bij huis, omdat die makkelijk in te vullen is
[M]
ja daar ben ik het wel mee eens, in Newcraft willen wij ons eerder richten op een hoger liggend doel
[D]
hoger liggend doel moet ik even over malen; NPS stond niet de challenge, meer een AEGON algemeen doel
[D]
'10% kosten besparen, ongelofelijke impact op een bedrijfsresultaat! 'maar dat is niet een discussie die we nu hoeven te voeren'
[M]
maar laten we die NPS dan pakken; kijken met welke onderdelen scoren we dan een NPS
[C] nog steeds stil..

[D] corrigeer waar ik tekort door de bocht ga maar de NPS is nog steeds van customer journey
- beginnen met journey
- als je niet naar de kosten kijkt heb je de blueprint niet nodig
- hoe ziet de journey er nu uit?
[M] je hebt de blueprint wel nodig, want als je naar implementatie gaat, dan moet je dit wel weten

[D] wat je dan doet; design doet die journey en flikkert hem over de muur naar data
- met de vraag; wie zijn dit eigenlijk
- kan je mee een profiel terug geven?
[C] voor mijn gevoel hinken we nu op twee gedachtes, ene zijds heel erg in die NPS en anderzijds heel erg weggestuurd, om kosten reductie uit te voeren voor AEGON

[D] maar kostenreductie is even geparkeerd.
[C] naja goed.

[A] wat denk jij dan cornelis? (want D stelde deze vraag niet)
[C] tttt is goed, nu begeef ik me op onbekend terrein, en ik ben juist geintereseerd?
hier komt dan wel een duidelijke disconnect naar boven;

[D] ik heb nog nooit relatie therapie gedaan, maar ik kan me voorstellen dat dit zo ongeveer gaat (grap)

[A] wat bedoel je dan precies met een disconnect?
[C] maar het is meer van; ik merk aan mezelf en dat het data team heel erg kan gaan denken, we gaan gewoon iets heels concreet,

Transcribt from audio recordings validation workshop - part 2

Appendix 7.2 - Thematic clustering validations

iets heel kleins oplossen, waarvan we de waarde ook heel erg concreet gaan proberen te maken, zo proberen te gaan bewijzen en dat is dan heel de casus.

Nu wordt het een stuk breder getrokken, wat wij eigenlijk zijn afgeleerd, omdat we vroeger altijd zo op de vingers werden getikt, daardoor verlies je namelijk grip; hoe kan je waarde aantonen.

En vaak is het maximaliseren van NPS, niet een voldoende KPI vanuit een data perspectief, daarom worden we altijd gedwongen in het vormpje om meer een ROI omzet gedregen waarde vermeerdereing aan te tonen.

NPS is bij ons meer een secundaire KPI, iets wat je in de gaten moet houden dat niet tever terug gaat als als je kosten aan het reduceren bent. Maar niet de kern van het geheel.

[A] zou jij dan nu zeggen, we gaan op die NPS focussen, we kijken hoe dat loopt?

[C] vanuit een data oogpunt, is een NPS een heel moeilijke metric om op te sturen, want hij wordt heel beperkt ingevult door klanten, vanuit data perspectief, hoe goed die NPS wordt gemeter, maar ook ingevult, van mensen die ook een nieuwe journey ervaren.

Ik bouw een tooltje, om mensen zoveel mogelijk via de website te laten funnelen, en daar al hun informatie te vinden. Om maar zoveel mogelijk te verkomen dat ze gaan bellen; is veel makkelijk te meten dat ze dan niet bellen. Sinds we dit hebben ingevoerd, zijn het gelijke aantal schade gevallen, maar 40% minder via de telefoon (+NPS is niet significant gedaald) en dan heb je hem dicht getimmerd.

Dus vandaar dat ik hier op vastloop, als we op NPS gaan zitten te focussen, vanuit data oogpunt hebben we een probleem om aan te tonen wat het doet.

[M] ik kan daarin je denken volgen hoor cornelis
[C] niet dat ik het niet eens ben, ik vind ook dat alles klantgedreven moet zijn (biologisch over denk), dat de klant tevreden is en AEGON meer verdient

- kans dat dit gaat falen groter dan dat het gaat lukken

[OB] hele hele lange stilte……

[M] ik denk dat dit ook wel een interessant ding blootlegt waarom..

- ook een uitdaging is om elkaar te blijven vinden C
- dat zie je ook in de manier waarop een design team vraagstukken voor ze kiezen krijgt
- dat zijn soms hele fuzzy dingen, die totaal geen concreetheid in zich hebben, en dat ontdek je juist met design

[C] waarde aantonen heel lastig voor data als het fuzzy is, D helpt daar heel erg bij bij verschillende projecten, om ons daarop te challenges, hoe maar je nou een goed KPI framework, connectie tussen inzicht en waarde

- is ook duidelijke uitdaging voor het data team

[D] om jouw challenge te challenge; het feit dat het voor het data team om iets direct te meten, wil niet zeggen dat je er niet indirect aan kan bijdragen,

- Citizen M; 1+1=3 (design en data, waar strategy het aan elkaar kletts); samen meer dan de som per delen
- data heeft allerlei subvragen beantwoord, die alles bij elkaar argumenten waren in een groter verhaal
- maar het was niet dat data naar 1 eindmodel kon toewerken]
- hoe data kan bijdragen aan een strategy of aan een design vraagstuk (zonder naar een deliverable toe te werken hoe ze dat wel doen, voorspelling models, rfm model) maar door kleine subvragen te beantwoorden die als een soort van proxy werken voor wat andere teams aan het doen zijn
- niet uiteindelijk weten hoe je het hele project optimaliseren, maar te drijven

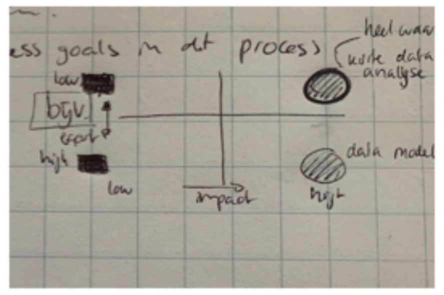
[M] als journey visualisatie enige deliverable was geweest bij citizenM, had ik juist andere probleem gehad

- citizenM; waar is dit op gestoeld/wat ga ik hier aan bijdragen? te weinig om als voldoende te accepteren, of als handvat voor meer (projecten

[D] effort en impact niet door elkaar halen
20 seconde werk; hoe groot is de kans dat iemand terug komt na 1e bezoek, 2e bezoek.
Na elk vervolg bezoek, werd kans groter en groter - extreem waardevolle impact
Hoe kunnen we dan iemand verleiden; om nog vaker terug te komen?

[C] input voor een journey / eigenlijk meer een soort argument om een journey te gaan vormgeven (om het doel van de journey te valideren)

- financieel vraagstuk: door te focussen op mensen die meer terugkwamen, kan je x euro verdienen
- kans dat iemand terugkomt = x% winst die je maakt na 3e bezoek is y€ - dus x*y = de waarde van het terug laten komen van de klant
- bereken dus de maximale kosten, om mensen na 3 keer terug te laten komen
- dat was bij citizenM een belangrijk inzicht
- input van data was; argumentatief en niet 1 vastomlijnd eind deliverable
- faciliterende rol van data



[C] daar ben ik het mee eens, maar ik kan nu niet zien hoe het terugkomt

invullen 2e template
[D] het normale data process, met validatie van data qualiteit, messcherpe afbakeningen KPI's

- andere granulariteit
- maar ook echt andere golflengte
  - data
  - design
- 1 faciliterend maken van de ander: niet stiekem proberen om allebei een deliverable op te leveren
  - design; data moet verrijken en onderbouwen van de keuzes die gemaakt worden
  - data; design moet helpen met input leveren (service blueprint om data helpen prioriteren waar nieuwe data solution opgeleverd gaat worden)

Nu gekozen; NPS te maximaliseren; to-be customer journey

- rol data; bewijslast leveren, prioriteit voor klantsegment
- alle inzichten, waardoor design gerichter te werk kan gaan

[A] wat zijn de belangrijkste touchpoints?
[C] elke phase wel eigenlijk?

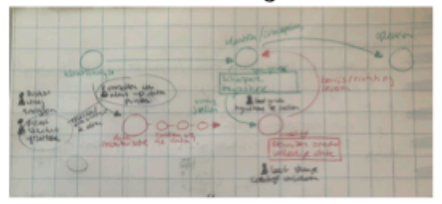
1. "als je die klantsafari doet aan het begin, hoe kan je klantervaringen vertalen naar datapunten, dus een soort van data inventarisatie"
2. en bij prepair; validatie wanneer hebben we genoeg data (vinkje zetten) om analyses überhaupt uit te voeren
3. uiteindelijk; prepare; stukje vanuit data science, zorgen dat alles goed staat en aan de bak kunnen
4. en tijdens create, is het uitvoeren van data voor analyses onder design vraagstukken / en inzichten te behoeven van ideation te doen (pingpongen)

[A] wat zijn de activiteiten tijdens het pingpongen?
stel, M heeft kans gespot, en die moet dan naar jullie?

[C] hypothese cyclus; ik denk xyz, kunnen we dat bevestigen met data?

Transcribt from audio recordings validation workshop - part 3

- als je nou al eerder die link heb gelegd tussen de data en design data points
- als je dan vervolgens, web gedrag aan gaat koppelen
- komt dan dat gedrag overeen met wat ik in me ideation heb gedefinieerd.



[D] heel belangrijk punt; waar het design team ingetrained kan worden, breng nou eens scherp onder woorden wat de hypothese is, zodat het data team echt kan helpen met het valideren van de hypothese

- dan mag het data team uitgedaagd worden; hoe kan je bij gebrekkige data, toch een bepaalde vooronderstelling kan vinden
- dat is iets waar beide teams elkaar echt kunnen versterken

[M] ja ja, dat gebeurd nu echt te weinig

[A] hoe gaan we dit dan doen, als we dit morgen moeten doen?
[D] citizenM is een voorbeeld daarvan, toen zat ik erbij vanuit strategy

- we zijn gewend uit een strategy project om aan het begin hypotheses te formuleren 'en toen ook vrij makkelijk een bakje met hypothesis neergelegd, zoek zelf maar welke data je nodig hebt en zoek het maar uit'
- een van de maturity modellen; die heb ik toen bij design neergelegd, jongens moet je kijken; iemand moet op ze minst 1 keer terugkomen, dan wordt die heel veel geld waard

Individuele vaardigheden die ervoor kunnen zorgen dat mense beter kunnen samenwerking zonder dat je strategy nodig hebt; als je hier beter in bent

- hypotheses formuleren
- creatief nadenekn hoe je hypotheses kan bewijzen
- ben je minder afhankelijk van een partij die er tussen zit

[D] ik zou hopen dat dat over tijd niet meer nodig is (de faciliterende rol)
[A] daarom heb je wel eerst iemand nodig die dit begeleidt

- framework is hetzelfde met de hypotheses

[D] heeft ook te maken met

- ontwikkeling van je eigen medewerkers
- commerciele component aan; als een designer weet hoe die met data kan samenwerken
  - met minder mensen een project doen
  - meer soorten projecten doen
- voor meer mensen is het interessant om dit te kunnen doen zonder dat er poppetjes tussen zitten

[M] ja absoluut
[D] eerste is het belangrijkste; het moet ook gewoon leuk zijn

- 'ik wil gewoon met cornelis samenwerking, ik heb nog nooit een project
- 'alleen workshops gedaan, en trainingen'

Samen reflectie

[A] reflecteren op de sessie

[D]

- data scientist zet hem even op scherp; wordt echt fundamenteel andere bril opgezet tijdens projecten
- de projecten waar we het over hebben gehad, waar de samenwerking goed ging, daar zitten hele interessante dingen die we moeten opslaan

[C]

- ik vond de discussie erg waardevol
- eigenlijk heb ik bij dit project, laten we dit gewoon gaan doen
- voor mij kunnen we zo'n casus vast wel ergens te vinden
- heel waardevol om zo met dit groepje te gaan zitten

[M]

- je ziet de manier waarop deze discussie gaat, dat we ook nog veel discussie nodig hebben
- en veel te weinig doen met elkaar
- ik denk dat; als cornelis en ik met elkaar hadden gezeten zonder daniel erbij, dat het veel moeilijker was geweest om uiteindleijk elkaar te kunnen aanvullen, dat daniel daarin een aantal dingen kan samenvatten, en meer twee kanten kan opdenken, en een andere reflectie geven op wat cornelis zegt
- Daniel; over de lange termijn zou gewoon iedereen elkaar moeten vinden, zonder dat er iemand nodig voor is

[D]

- als je kijkt naar waar designers vanuit huis goed in zijn, is dat abductief (divergent)
- data;
- als je elkaar wilt vinden; abductief (divergerend) + inductief en deductief (convergent) dan moet je daar een middenweg in vinden; abductief denken = middenweg
- als je data en design wilt laten samenwerking; 1 is in de lead voor het eindproduct, de ander is daar faciliterend aan. Heipalen voorbeeld; 1 is niet minder belangrijk dan het ander (citizen M verhaal)

[M]

- allemaal losse delen die het een optelsom hebben gemaakt van meer

[M]

- heb je in jouw project ook van dit soort voorbeelden uitgeplozen?
- persona's voor KLM waar we van kunnen leren; waar data juist in de lead was

Transcribt from audio recordings validation workshop - part 4

4528

DESIGN FOR our future

TU Delft

IDE Master Graduation

Project team, Procedural checks and personal Project brief

This document contains the agreements made between student and supervisory team about the student's IDE Master Graduation Project. This document can also include the involvement of an external organisation, however, it does not cover any legal employment relationship that the student and the client (might) agree upon. Next to that, this document facilitates the required procedural checks. In this document:

- The student defines the team, what he/she is going to do/deliver and how that will come about.
- SSC E&SA (Shared Service Center, Education & Student Affairs) reports on the student's registration and study progress.
- IDE's Board of Examiners confirms if the student is allowed to start the Graduation Project.

USE ADOBE ACROBAT READER TO OPEN, EDIT AND SAVE THIS DOCUMENT

Download again and reopen in case you tried other software, such as Preview (Mac) or a webbrowser.

STUDENT DATA & MASTER PROGRAMME

Save this form according the format "IDE Master Graduation Project Brief_familyname_firstname_studentnumber_dd-mm-yyyy". Complete all blue parts of the form and include the approved Project Brief in your Graduation Report as Appendix 1 !

family name: Luijt

initials: NA   given name: Nick

student number:

street & no.:

zipcode & city:

country:

phone:

email:

Your master programme (only select the options that apply to you):

IDE master(s): ( ) IPD ( ) Dfl (●) SPD

2nd non-IDE master:

individual programme: - - (give date of approval)

honours programme: ( ) Honours Programme Master

specialisation / annotation: ( ) Medisign

( ) Tech. in Sustainable Design

( ) Entrepeneurship

SUPERVISORY TEAM **

Fill in the required data for the supervisory team members. Please check the instructions on the right !

** chair: Rebecca Price   dept. / section: MCR

** mentor: Barend Klitsie   dept. / section: MCR

2nd mentor: Maik de Rooij

organisation:

city: Amsterdam   country: Nederland

comments (optional): While both are from MCR, they complement each other due to the two main fields in this project: innovation process (and methodology) and organisation design. Rebecca brings great value in the first with her expertise in design strategy and social technical systems (including experience how to combine this with data looking at her papers). Barend enables me to unfold that process into the context of advisory organisations with his expertises in organisational design, the management of innovation and his experience in the consulting market.

Chair should request the IDE Board of Examiners for approval of a non-IDE mentor, including a motivation letter and c.v..

Second mentor only applies in case the assignment is hosted by an external organisation.

Ensure a heterogeneous team. In case you wish to include two team members from the same section, please explain why.

TU Delft

Procedural Checks - IDE Master Graduation

APPROVAL PROJECT BRIEF

To be filled in by the chair of the supervisory team.

chair ____ date - - ____ signature ____

CHECK STUDY PROGRESS

To be filled in by the SSC E&SA (Shared Service Center, Education & Student Affairs), after approval of the project brief by the Chair. The study progress will be checked for a 2nd time just before the green light meeting.

Master electives no. of EC accumulated in total: ____ EC

Of which, taking the conditional requirements into account, can be part of the exam programme ____ EC

List of electives obtained before the third semester without approval of the BoE

( ) YES all 1st year master courses passed

( ) NO missing 1st year master courses are:

name ____ date - - ____ signature ____

FORMAL APPROVAL GRADUATION PROJECT

To be filled in by the Board of Examiners of IDE TU Delft. Please check the supervisory team and study the parts of the brief marked **. Next, please assess, (dis)approve and sign this Project Brief, by using the criteria below.

- Does the project fit within the (MSc)-programme of the student (taking into account, if described, the activities done next to the obligatory MSc specific courses)?
- Is the level of the project challenging enough for a MSc IDE graduating student?
- Is the project expected to be doable within 100 working days/20 weeks ?
- Does the composition of the supervisory team comply with the regulations and fit the assignment ?

Content: ( ) APPROVED ( ) NOT APPROVED

Procedure: ( ) APPROVED ( ) NOT APPROVED

comments

name Monique von Morgen   date - -   signature

Initials & Name: NA Luijt   Student number: 4381092

Title of Project: Data-driven Innovation

Data-driven Innovation — project title

Please state the title of your graduation project (above) and the start date and end date (below). Keep the title compact and simple. Do not use abbreviations. The remainder of this document allows you to define and clarify your graduation project.

start date 21-09-2020 — 29-03-2021 end date

INTRODUCTION **

Please describe, the context of your project, and address the main stakeholders (interests) within this context in a concise yet complete manner. Who are involved, what do they value and how do they currently operate within the given context? What are the main opportunities and limitations you are currently aware of (cultural- and social norms, resources (time, money,...), technology, ...).

Context
The project takes place between IDE, TU Delft and consulting organisation [redacted] an advisory organisation that helps organisations transform to this digital age. The project involves three internal teams: Creative (Design), Strategy & Data Science.

Introduction
Design thinking in the past decades has been widely recognized as a tool to innovate for organisations (e.g. Gruber et al., 2015) to differentiate from competitors and driving business performance (Liedtka, 2015). Design thinking has three core principles: human centeredness, abductive reasoning and iterative process (e.g. Verganit et al., 2020).

But in recent years we also have 'entered the golden age of digital innovation' (Fischman et al., 2014). Meaning digital technologies are increasing impact in companies' management of innovation (Trabucchi, 2019). One of those digital technologies, and potentially the most impacting of them all (Verganti et al., 2020), is the field of data science: a set of fundamental principles that guide the extraction of knowledge from data. (Provost & Fawcett, 2013). Two different disciplines both driving companies' capability to innovate, yet synergies between both disciplines have yet to emerge (Duan et al., 2020). Although recent scholars have started to research this topic, the foundation of academic literature on this topic is scarce.

Verganti, Vendraminelli, and Iansiti (2020) argue that AI not only incorporates the three essential principles of design thinking (human centeredness, abductive reasoning/creativity and iterative process) but outperforms human-centered innovation by eliminating human-intensive limitations. They suggest that in big-tech driven firms, problem solving will be replaced by computers and designers will shift their focus to problem finding. Kun and Kortuem (2020) argue that designers can use their abductive reasoning during exploratory data analysis in order to generate hypotheses. While both imply a changing role for designers towards the start of the innovation, one was conducted with master level students and the other based on big-tech driven firms. The question remains if both are applicable to other contexts. As in the context of this research: designers in consulting organisations with in-house data scientists providing digital innovation.

Further, without understanding how this change could practically be adopted by the consulting organisations housing those designers, the impact will remain at a theoretical level. How should consulting organisations transition towards this change? What capabilities are required to do so? Triolo, De Luca and Guenzi (2017) argue that within incumbent firms, service innovation benefits from data-rich environments (Triolo et al., 2017) and propose seven influential organizational factors (e.g. top down management, customer centric culture or agile processes). Although first research has been done on these organizational factors, academic foundation is scarce and again questioned to be applicable to the context of consulting organisations.

To conclude, although first scholars have started exploring the future role of design in data driven innovation and how consulting organisations need to be designed, there remains much to explore and there are questions regarding context sensitivity. These questions are the basis of my research: how can consulting organisations use data science in their current design-driven innovation process?

For digital innovation consultants [redacted] using designers as well as data scientists, a better understanding of how synergy can emerge between these two fields is of high value. This would allow them to design their organisation in order to stay relevant to their clients and achieve a sustainable competitive advantage. Strategic designers working in these organisations, need to understand how they can become relevant in a future where their own position is under pressure. Positioning themselves in this digital age and playing a relevant and significant role in the future of innovation.

Opportunities
First, both my chair and mentor provide support of academic knowledge and the freedor [redacted] has an open culture towards researching the company and offers its internal knowledge [redacted] with clients and co-workers in order to validate prototypes during this project

Limitations
The project has a time limit of 100 days. First this limits me to design only relevant elements of the business (as designing everything is never possible), which could challenge the practical applicability of the solution in the company. While designing should always come from a holistic perspective, the impact to other parts can be reflected on. Second a longitudinal study is not possible in order to prove the actual success of improvements.
Last, in this time of Covid-19 most of the research will be done digitally. e.g. during internal and external interviews the 'thickness' of the descriptions could be limited as observations are less possible.

space available for images / figures on next page

PROBLEM DEFINITION **

Limit and define the scope and solution space of your project to one that is manageable within one Master Graduation Project of 30 EC (= 20 full time weeks or 100 working days) and clearly indicate what issue(s) should be addressed in this project.

The scope of this thesis is consultants with design thinking at the core of innovation putting effort to integrate data science in this innovation process.

The issue is that designers are missing out on the opportunity to tap into the promises that the field of data science and its techniques brings. Also, the companies that have those designers working as innovators, are not using the potential the synergy between both could bring. As digital techniques (and data science specifically) are going to increasingly impact innovation, without providing designers and companies the handles to work with data scientists, design as a discipline could become less relevant in the future of innovation.

ASSIGNMENT **

State in 2 or 3 sentences what you are going to research, design, create and / or generate, that will solve (part of) the issue(s) pointed out in "problem definition". Then illustrate this assignment by indicating what kind of solution you expect and / or aim to deliver, for instance: a product, a product-service combination, a strategy illustrated through product or product-service combination ideas, ... In case of a Specialisation and/or Annotation, make sure the assignment reflects this/these.

How can consulting organisations use data science in their current design-driven innovation process?

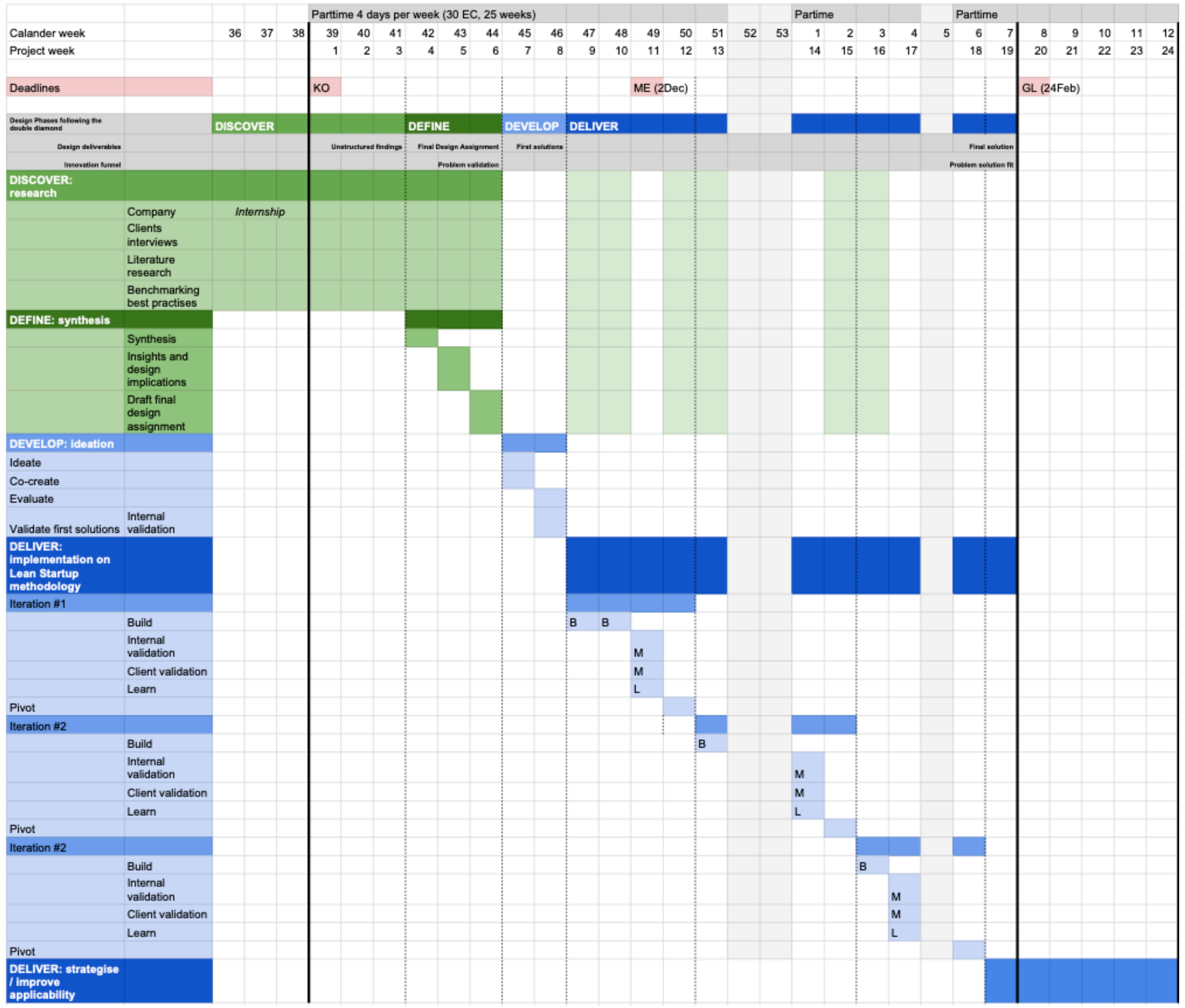
Sub questions
1) What are the conditions for a successful integration of data science in a design-driven innovation process in a digital service innovation consulting?
2) What are the capabilities of consulting organisations that influence this integration?
3) How should the organisation be designed in order to adapt to this change?
4) What should the future role of designers be in these organisations
5) How do they collaborate with data scientists in this digital innovation?

I expect to deliver a proposed new business design o [redacted] Implying, what parts of the company have to change in order to maximize the potential of innovating by using data science in design. This new design is complemented by action steps in a roadmap of how to get there and a set of recommendations.

PLANNING AND APPROACH **

Include a Gantt Chart (replace the example below - more examples can be found in Manual 2) that shows the different phases of your project, deliverables you have in mind, meetings, and how you plan to spend your time. Please note that all activities should fit within the given net time of 30 EC = 20 full time weeks or 100 working days, and your planning should include a kick-off meeting, mid-term meeting, green light meeting and graduation ceremony. Illustrate your Gantt Chart by, for instance, explaining your approach, and please indicate periods of part-time activities and/or periods of not spending time on your graduation project, if any, for instance because of holidays or parallel activities.

start date 21-09-2020 29-03-2021 end date



The approach is based on three methods: the Double Diamond (UK Design Council, 2004) , the Lean Startup (Ries, 2011) and Business Design (Fraser, 2012). It can be argued that all three methods have common similarities, as both the lean startups as business design are built on the core principles of design thinking: human centeredness, abductive reasoning and an iterative process.

The double diamond is the foundation for the entire structure, consisting of four phases to discover, define, develop and deliver (UK Design Council, 2004). Second, the build-measure-learn loop (Ries, 2011) of the Lean Startup is used during the deliver phase. Last, during the delivery phase Business Design is integrated with the 'third gear', strategic business design: 'align broad concepts with future realities through strategy formulation and design of the business model itself' (Fraser, 2012).

MOTIVATION AND PERSONAL AMBITIONS

Explain why you set up this project, what competences you want to prove and learn. For example: acquired competences from your MSc programme, the elective semester, extra-curricular activities (etc.) and point out the competences you have yet developed. Optionally, describe which personal learning ambitions you explicitly want to address in this project, on top of the learning objectives of the Graduation Project, such as: in depth knowledge a on specific subject, broadening your competences or experimenting with a specific tool and/or methodology, ... Stick to no more than five ambitions.

During my period of study but especially during my internship at Fronteer I sometimes witnessed the lack of innovation power of just Strategic Design, where sometimes it was put as 'fun ideas'. For me this was mainly due to two things, the lack of implementation at the companies itself and the lack of technical and digital understanding.

My three drivers behind this project are 1) contributing to the field of (Strategic) Design and strengthening the position it has 2) becoming more relevant as a professional and 3) having the ability to achieve greater impact on businesses.

I want to prove the skills I acquired during different stages during my education. First Strategic Design, which is rooted in the essence of my MSc Programme. Second, my capability of how Innovation should be implemented in an organization, which I mostly developed during my internship at Fronteer. Last my lean mentality, which I implemented during my master elective 'Build your Startup' to develop my own startup.

The competences I am most eager to learn are twofold: Business Design and Data Science. I aim to acquire Business Design as my future specialization in a T-profiled Designer. Where my current skills are strategic and qualitative, I want to acquire more operational & more quantitative skills. I aim to achieve this by doing two things: the operational skills by doing extensive literature research and the quantitative skills by reading literature and using business tools during prototyping. I aim to acquire knowledge on Data Science as a crucial part of my broader knowledge as a T-profiled Designer. I perceive data analytic capabilities as a necessary thing to be more relevant as a professional in this digital age.
This will be done in three ways: an data science online course, during literature research and co-creating with data scientists.

My main two personal ambitions are acquiring in depth understanding of the dynamics in the consulting market and improving my skills in managing multidisciplinary teams. Both I expect to learn while doing the project itself. During research and [illegible]d to interview both sides, employees (the strategy, creative and data science teams) a[illegible]nts.

FINAL COMMENTS

In case your project brief needs final comments, please add any information you think is relevant.