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Data Science for Service Design: An exploration of methods

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Abstract: This research identifies the opportunities for data science to support the service design processes through explorative development of a guide to data science methods for service designers. Designers and their teams search for data science techniques from their perspective as designers, while current literature is fragmented and technical. The present research explores methods that can help designers get started with data science. It evaluates if the techniques meet the designer's needs and fit the design process with user-centred activities; as a result, the methods contribute to the diversity of the designers' methods toolkit. These methods increase the validity of user research, make hidden information accessible with specialised user research tools and help designers in their creative process through relevant resources, inspiration and/or an alternative perspective. Together these results encourage organisations to mature data science resources for design projects so that their services benefit from more informed designers.

Keywords: service design; data science; process mining; mixed methods

1. Introduction

Services are central to value creation (Vargo and Lusch, 2004; Grönroos, 2011; Secomandi & Snelders, 2011) and service innovation has a crucial role in economic and social development (Patrício, Gustafsson & Fisk, 2018). The growing consumers' demands and increasing complexity of technology puts pressure on service providers to improve the quality of their services (Spiess, T'Joens, Dragnea, Spencer & Philippart, 2014). Service design has the potential to foster the development of superior services experiences, supporting the value co-creating interactions between the service provider and user (Costa, Patrício, & Morelli, 2018; Patrício et al., 2018; Kimbell, 2011). The growing demand for service quality and technological advancements also puts pressure on the service designers, and academia and industry call for interdisciplinary methods to support the development of superior service experiences (Patrício, Fisk, Falcão e Cunha, & Constantine, 2011).

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Data science offers opportunities for designers, as it helps extract meaningful knowledge from data (van der Aalst, 2014) in a context where the amount of data from and about consumers grows - e.g., consumer-generated content (Xiang, Schwartz, Gerdes Jr, & Uysal, 2015). Discipline such as marketing (Murray, Agard, & Barajas, 2018; Tan, Steinbach, & Kumar, 2006), product design (Köksal, Batmaz, & Testik, 2011) and ethnography (Weibel et al., 2013) already apply data science quite extensively. Data science techniques have also proved useful for projects closer to service designers, such as, among others, mapping the customer experience (Bernard & Andritsos, 2017), and understanding social and economic behaviour (Xiang et al., 2015).

Yet, although these studies provide useful insights, literature is fragmented over multiple areas such as process mining (van der Aalst, 2011, Bernard & Andritsos, 2017) and natural language processing (Balazs & Velásquez, 2016; Poria, Cambria, & Gelbukh, 2016). Furthermore, to our knowledge, these studies are not specifically focused on service designers, nor they explicitly address designers' needs. Many design agencies, service designers and their teams look for ways for utilising these data science techniques from their perspective. This research aims to provide key information in an overview of when and how data science is useful to support the service design process. The explorative, qualitative research process resulted in a guide to service design methods based on data science techniques.

1.1 Research focus

This research brings service design and data science together to explore the possibilities and answers the following research question: *When and how can data science be used to support service designers?* The objective of this research is to help service designers navigate and select data science techniques for their projects. As such, it is essential that the research meets the needs of the designer and fits the service design process. More specifically, we refer to the difference between a technique as a way to execute (doing it right) and methods as procedures to achieve an objective (doing the right thing; Junginger, 2015). The data science techniques are addressed by this research on the feasibility and theoretical background. However, the focus of this research is how they apply as a method for designers to accomplish their goals.

Accordingly, this research (1) includes both academic and practitioners (i.e., digital agency Mirabeau¹) perspective; (2) conducts an explorative and qualitative research from the perspective of the designer (e.g. test desirability); and (3) examines data science techniques/tools, custom build projects and data experts (e.g. indirect use by tool).

1 Mirabeau is a digital agency with clients in multiple fields, such as B2B, finance, retail and travel (Mirabeau, n.d.), and practises (digital) service design.

1.2 Background

Service design offers a unique perspective to service innovation and development, focusing on the service offering, and on the value co-creating interactions between the service provider and users (Costa et al., 2018; Patrício et al., 2018; Forlizzi & Zimmerman, 2013). Therefore, service designers model the holistic experience and the service environment (Yu & Sangiorgi, 2014; Zomerdijs & Voss, 2010), which contains social, material, relational elements (Zomerdijs & Voss, 2010; Kimbell, 2011). Service designers work typically with user-centred methods, where multiple stakeholders from different organizational silos collaboratively to-develop the design solution (Evenson & Dubberly, 2010; Stickdorn, Schneider, Andrews & Lawrence, 2011).

On the other hand, the growth and significance of data in our world is clear. Data is a valuable resource that produces new insights and competitive advantages because it originates from the customer (Witten & Frank, 2005). Data science embodies the fundamental principles that support and guide the extraction of knowledge from data (Provost & Fawcett, 2013). It is a tool for explaining data and making predictions. Data science contains mining techniques and contextualising fields (e.g. visualisation) (van der Aalst, 2014), and is the process of automatically discovering and describing meaningful patterns in big tabular data (Tan, Steinbach & Kumar, 2006; Witten & Frank, 2005) or data logs (van der Aalst, 2014).

1.3 Stakeholders

This research is aimed at the service designer that practises service design as defined in the previous section. They work for e service providers, its stakeholders and users with a solid base in the philosophy of human centeredness. We also include “digital designers” and other designers that deal with, for example, both service and interaction. Nonetheless, the presented techniques and methods could still be interesting for managers and other professionals interested in the techniques and methods of service design.

This paper acknowledges the differences between data roles, such as data scientist, data analyst and quantitative researcher. In this realm there are variations on the technical level and expertise. For example, the data scientist should have higher data management skills than an analyst (Davenport, Barth & Bean, 2012). The quantitative user researcher is not specified on this scale and is specialized on processing user related data. This paper will not elaborate further on the differences between these roles. The focus is on applying data sciences techniques in a broad scope from custom to indirect in a tool. Therefore, methods are not limited to the technical level of the data role; which role is desired depends on the method and available/required resources.

2. Research process

This research examines how data science can support service designers by mapping methods based on data science techniques through an iterative research process where both

academic and practical designers were involved in user-centred activities (Saikaly, 2005). The research process alternated between converging and diverging activities and is divided into three main phases: exploration, ideation and evaluation. Throughout these phases, the research explored the methods by emerging, splitting, merging, terminating and changing.

Figure 1 Photo of the pilot evaluation workshop. The participant compared personal and data science methods.

The first phase of the research, namely exploration, focused on the characteristics, possibilities and opportunities for the intersection between the fields of data science and service design. The goal of this phase was defining the research areas, understanding designers and data scientists, and creating a mental structure of the designers' needs and data science strengths. Key activities at this phase included shadowing, interviewing, and literature review.

As the opportunities for the use of data science in supporting service design grew, they were pruned in the ideation phase, resulting in a guide to methods that use data science and collaboration. At this point, case studies and speculative cases helped to refine the ideas with the help of design practitioners. Main activities in this phase consist of brainstorm methods and feedback sessions with designers.

The evaluation phase aimed at testing the usability and desirability of the methods and gathering overall findings from the design research. Workshop sessions with designers (Figure 1), self-reflection, discussions and a panel interview substantiated this phase.

3. Service Design and Data Science

3.1. Opportunities

Most opportunities for data science to support service designers are based on providing easier, new or different sets of information. Designers use research and analysis methods to “organise, share, discuss and make sense of the data they collect to generate insights” (Costa et al., 2018, p165). The variety of methods is essential to support designers to achieve holistic and valid observations, and to ensure applicability and quality in a range of projects. Moreover, because every method has weaknesses and limitations, triangulation can help mitigate blind spots in the research process (Figure 2), increasing the reliability and validity of the findings (Jick, 1979; Creswell, Plano Clark, Gutmann, & Hanson, 2003).

Figure 2 The reliability and validity increase with method triangulation.

Applying data science in a design context may provide new and advanced methods to the existing method toolbox of service designers. Service designers gain insights based on the combination of qualitative and quantitative information (Stickdorn et al., 2011). The data science techniques are mainly quantitative-based and complement with the designers' traditional use of qualitative methodologies. Next to additional quantitative analyses, data science contributes new perspectives to designers with another way of working. Various knowledge representations and learning techniques can result in alternative conclusions. The learning techniques make it also possible to predict or pick up seemingly small signals from the data or process large amounts of data.

3.2 Challenges

Changing the way of working in the organisation is a complex and difficult feat. This transformation can be assisted by a maturity model that identifies the steps in the process of embedding new methods (Corsten & Prick, 2019). This research proposes extending the service design maturity model of Corsten and Prick (2019) to the ability of combining data science and design in relation to methodology-independent stages (Table 1).

Based on these stages, the research identified three types of challenges: technical, determining business value and capabilities.

Table 1 Stages of the Maturity Model. Extracted from the Service Design maturity model of Corsten and Prick (2019).

Explore	Prove	Scale	Integrate	Thrive
This first stage is about trying the new methodology and starting the initiative.	The second stage should create evidence of value and lay the foundations.	Next, the capabilities spread outside the initial team and through the organisation.	This stage systematically integrates the methodology in the way of working.	Ultimately, the methodology ingrains into the company culture and pushes the field.

In the early stages (Explore and Prove), some *technical* data-related challenges arise, such as the lack of data availability, the data quality or access to the data. Furthermore, finding suitable data is a significant challenge since the needs and specific wishes of the designer change during the project process. In the Scale stage, the capabilities spread outside the initial team. Applying more and particularly more complex quantitative methods will demand different skills from the design team. Team members will need a shared knowledge base, and the user researcher might need additional skills in data science or quantitative research. Finally, throughout all stages, showing the value of the transformation is essential (Corsten & Prick, 2019). However, proving business value might be most difficult when the value still depends on individual projects.

3.3 Service Design Process model

The design process is a non-linear iterative process of diverging and converging. Although it is circular, different phases can be represented in a general structure (Stickdorn et al., 2011) similar to the double diamond model of British Design Council from 2005 (Yu, 2017). In this paper, we adapted the double diamond (DD) into the holistic double diamond (HDD). This adapted model contains two diverging and converging diamonds similar to the DD, but it also considers a broader timeline that supports mapping the data science methods for the service design process in a clearer way.

Figure 3 The Holistic Double Diamond model.

The HDD model places Implement out of the second diamond and accommodates an explicit Test phase. This research makes testing explicit to demonstrate the different needs and possibilities for designers. Additionally, ideation is a diverging process, while testing is not. Testing is converging, and the DD does not address this contrast. Secondly, the HDD includes the designer's activities and involvement outside the scope of the DD and similar models; the outer phases Prepare and Maintain.

Prepare: Prepare is the phase that involves the activities of the service designer before kickstarting the project, such as preparing the service design process and perhaps explaining what service design is to the client (Stickdorn et al., 2011). In this phase it is decided that and in which direction the project takes place. The main goal of this phase is preparing for the process and project, e.g. with pitches and stakeholder convincing.

Maintain: The end phase is Maintain, where designers continue assisting the services without starting a new project. After implementing the service concept, design activities take place to continue and improve the service. In this phase, the service is measured to learn and increment.

Table 2 Design phases of the Holistic Double Diamond model. Horizontal axis: phases over time; Vertical axis: **Phase**, description, phase in similar models.

Prepare	Understand	Define	Ideate	Test	Implement	Maintain
This phase prepares the process and project so that there are directions and resources to start.	The designer explores the problem space for the true problem and creates a holistic view.	Findings from the analysis are concluded in the creative brief. The problem is (re)framed.	Concepts are developed with an iterative process for creating and refining solutions.	Testing is essential to evaluate the trials with prototyping, user tests and reflection.	The service concept is realised and launched.	This phase continues and improves the service(s) after implementing the service concept.
Kick-start	Discover, Analyse, Explore, Research	Frame	Develop, Generate, Create	Prototype, Reflect, Evaluate	Deliver, Launch	Optimize

4. Data science methods for service designers

Through practice-based design research (Saikali, 2005), this research explored how data science may support service design processes through the identification and analysis of concepts of data science methods for service designers. The methods are categorised into four groups: 1) user research tools, 2) analysing complex systems, 3) inspiring and insightful generated materials for serendipity, and 4) joining forces with data scientists in collaboration. Because designers experience different needs during a project, and data science offers new ways of providing insights, analysis, inspiration and collaboration. The methods connect with these different needs and excel at different phases in the design process which are discussed in Section 3.3. (Figure 4).

Figure 4 Methods in the service design process. The most relevant phases of each method are highlighted. The design process model is a modification of the 'double diamond' by British Design Council in 2005 (Yu, 2017).

4.1 User research

Data mining can make hidden information accessible to designers with specialised user research tools, and therefore designers can measure more factors of users. For example, the following two methods (M1 and M2) can be particularly useful to uncover users' insights.

M1: Opinion mining analyses sentiment and correlations in consumer-generated content that is relatively easy to obtain such as social media, reviews and customer feedback. The method informs the designer about the users' satisfaction, frustrations and celebrations. For example, text can be classified as positive/negative and other emotional states (Balazs & Velásquez, 2016) or analysed for relations between extracted factors and ratings (Xiang et al., 2015). The advantages compared to interviews and surveys is that no explicit participants are needed, and the opinion is provided in a non-experimental setting.

M2: Bio translations is a group of research tools that analyse the inner state of users by interpreting (seemingly unmeasurable) signals. Depending on the recording device (from EEG to facial recognition), the technique can be noise sensitive or intrusive in use. For example, Zhou et al. (2017) used passive RFID tags and classification models to detect customer actions on clothing, such as pay attention to, pick out and turn over. This way, they detected how customers browse stores. During the evaluation workshop, an abstract layer with classified mental states was preferred over factual data.

4.2 Systems

Process mining can support designers to understand and test system models, such as mapping the actual and expected customer journey.

M3: Processing mining can generate, analyse and test models of complex systems such as the actual and expected *customer journey*. Designers can with this approach 1) extract information from the real world, 2) gain insight into the common and specific cases and 3) simulate environments through virtual models. For example, Harbich et al. (2017) extracted individual journeys from event logs of the daily activities of Chicago citizens to detect the most likely and also alternatives/divergent journeys.

4.3 Serendipity

Data science can help designers in their creative process through relevant resources, inspiration and an alternative perspective. The materials involved in the design projects (e.g. artefacts and insights) can be analysed for high-level or cross-domain insights or generated by machines.

M4: Data-driven techniques can assist with finding and exploring relevant patterns and resources from projects, clients and designers. Build into a data-driven system; designers can analyse their materials and insights for higher-level or cross-domain insights and spread knowledge faster through the organisation. The performance depends highly on the quality of the content. The system can be used for kick-starting, on-boarding, inspiring and data-driven design projects.

M5: Generating (parts of) design artifacts by machine learning helps designers with inspiration, additional information or efficiency. It can produce an alternative perspective or autocomplete for prototypes, testing and personas. The difficulty with generating personas is defining their attributes and selecting the matching data sources.

M6: Segmenting can reveal patterns and form groups based on non-predefined characteristics. This provides an alternative view on the users or products because unexpected or previous unknown user behaviour can be found. The results as qualities (sexting correlates to user blocking²) and quantities (80% of users spend more than 10% of their total clicks on blocking events²) are useful for the designer as an insight but also evidence and foundation for non-traditional segments. The technique requires that the data is rich enough to capture underlying behaviours and prevent self-fulfilling prophecies. During the evaluation workshop, designers showed the most interest in behavioural- and emotional-based segmentation.

4.4 Collaboration

The design team can work together with data scientists more effectively with these collaboration methods that are not based on specific data science techniques.

M7: When collaborating in a team, the designer can request information from the data scientist in a broad sense (explorative) and for detailed information and validation.

M8: The effectiveness and meaning of data science techniques can be increased with the skills of service designers, such as to design value-creation and acquire a holistic view.

M9: Visualisations are a familiar tool for designers and service design has a highly visual approach (Costa et al., 2018). Relevant data can also be visualised for effective communication, organising, understanding, reasoning, decision making and displaying correlations (van der Aalst, 2014a; Costa et al., 2018).

5. Discussion

This qualitative, explorative study resulted in a guide to data science methods for service designers that contribute to the diversity of the designers' methods toolkit, and the main findings include:

- Integrating data science techniques requires organisational maturity.
- Data science techniques can increase the validity of user research with method triangulation.
- Data science can make hidden information accessible to designers with specialised user research tools and methods.
- Data science can help designers in their creative process through relevant resources, inspiration and an alternative perspective.

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

Together these results have the potential to enhance the methods toolbox of service designers and encourage organisations to mature their data science resources and capabilities for design projects. Service design and user-centred design fields can benefit from these developments, by becoming more informed about the users, stakeholders and applications. Furthermore, new challenges, employment and consulting for data scientists arise to support the advancing designers' needs.

5.1 Integrating data science and design projects

Integrating data science into design projects will change the roles within design teams and user research. Since a knowledge base on quantitative research skills is added to the team, they might need to acquire new specific (quantitative) research roles. The increasing diversity of skill sets will improve the available methodologies, but also requires a new way of working.

Furthermore, integrating data science techniques requires organisational maturity in data science. This will require investments and will lead to new opportunities for growing teams and companies. With the advancement of maturity, the availability and quality of data for service designers will grow and improve the designs they make. Addressing the maturity of clients is also essential for (design) agencies. Because they depended on the data and resources of their client, the agency can consult on data, data science and the integration with design.

5.2 Robust user research

More advanced user research tools become available, and design teams can create a better understanding of user behaviour and their inner states. Also, the implementation of services could be improved with a better comparison between the actual and expected journeys. Design teams should critically look at their user research and check if data science can fill their triangulation gaps and make their research more effective. For example, the design team should fully cover the behavioural-attitudinal and quantitative-qualitative axes. As a result, the designers' insights and methodologies are more robust.

5.3 Creative design process

Data science can help designers in their creative process with new user insights, generative design and alternative perspectives. With generative design, more digital creative tools become available, such as an autocomplete, and stimulate for a more efficient design process. The data-driven analyses result in new higher-level insights about the users and designers, while other data science analyses of users provide insights based on a different perspective. For example, non-traditional segments based on behavioural patterns provide alternative user-groups. This will improve the service design process itself as designers utilise more and/or better resources. Therefore, the design process will be based on more data and more diverse perspectives.

6. Conclusion

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

Service designers use particular methods to collect and analyse information for creating a holistic view of the users and stakeholders. Data science contributes by adding techniques for accessing new insights and/or increasing validation by supporting method triangulation. The techniques analyse for patterns, correlations and/or answer contextual or specific questions.

As shown on Figure 4, data science can be applied during the whole design process. It makes sense that data science techniques fit research-heavy phases of the service design process. However, this research showed that data science has the potential to support designers outside that scope extending to the whole project by, for example, helping stimulate inspiration during the ideation phase.

Data science supports user research in both foundational and directional research. User research is vital for analysing the holistic experience, and service designers benefit from specialised research tools to reveal new information about the users. Secondly, data science can help with the fast collection of materials that designers gather and build by finding patterns, highlighting elements and analysing insights. This approach is useful to support cross-team knowledge.

Challenges for using these concepts and methods seems to be mainly related to organisational maturity. Selecting a matching technique (including the data) depends on many factors, which are described in the detailed method description. For example, the required capabilities, such as skills and data, differ per technique.

This research was an explorative study and presented a broad overview. The concepts were related to the needs of designers and available project resources. The results were useful to orient and select data mining techniques for service design projects, but the findings can't be generalised.

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

To conclude, an overview was provided of data science techniques for service designers and their design process. Where fragmented literature might provide useful insights, this study offers validation with service designers or explicitly addresses their needs. The overview and the methods assist design agencies, service designers and their teams in organising, selecting and utilising these data science techniques.

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