THE DESIGN JOURNAL
2022, VOL. 25, NO. 2, 186–204
https://doi.org/10.1080/14606925.2022.2042108

Data science for service design: An introductory overview of methods and opportunities

Youetta Kunneman[a], Mauricy Alves da Motta-Filho[a] and Jasper van der Waa[b,c]

[a]Design, Production and Management, University of Twente, Enschede, The Netherlands; [b]Human Machine Teaming, TNO, Soesterberg, The Netherlands; [c]Interactive Intelligence, Technical University of Delft, Delft, The Netherlands

ABSTRACT

To support effective and successful projects, Service Design practitioners rely on insights that mainly build on qualitative research methodology. The literature on data science promises to help transform how design research is done, adding sophisticated quantitative analyses, complementing existing methods with the power of machines. Due to this potential, data science receives widespread attention from both design practitioners and academics. However, the literature is fragmented and specialized, making it hard for designers to engage with data science. This paper addresses the opportunities and challenges for data science to support Service Design projects, evaluating existing technologies from designers' perspective and providing an entry-level guide for service designers. These methods can help increase the quality of design research, making hidden information accessible and assisting creative processes. Together, these results are expected to inspire organizations to advance their data science resources for Service Design projects.

KEYWORDS

service design, data science, data mining, service design methods, practice-based design research

Introduction

Growing competition - driven by globalization and market deregulation - increasingly forces organizations to seek new sources of competitive advantage, resulting in increasing attention to the customer experience and consequently to Service Design. Service Design is a design discipline (Manzini 2009; Cross 1982) capable of fostering service innovation (Ostrum, Iacobucci, and Morgan 1995) and user and customer centricity (Wetter-

CONTACT Mauricy Alves da Motta-Filho m.alvesdamottafilho@utwente.nl Faculty of Engineering Technology, University of Twente, Horst Complex, W246, P.O. Box 217, 7500 AE Enschede, The Netherlands

Edman 2011), which involves stakeholder from both within and beyond the organization (Kimbell 2009; Miettinen 2016), supporting the development of the customers' value co-creation interactions (Costa, Patrício, and Morelli 2018; Patrício, Gustafsson, and Fisk 2018; Kimbell 2011) through the application of interdisciplinary and collaborative methods (Patrício et al. 2011).

Like many design disciplines, Service Design borrows methods from more established methodologies (Cross 1999). Qualitative methods, such as interviewing, observation, desk research and ethnography (Merriam and Tisdell 2015), are widely used in Service Design projects (Stickdorn and Schneider 2010), while the use of quantitative methods is much less common (Dribbisch et al. 2013). More recently, data science has emerged as a source of new and exciting opportunities for design research (Grimes et al. 2018; Chhabra and Williams 2019).

Data science refers to the study of data. In this paper, a 'data product' perspective will be taken (Cao 2017), in which data science is understood as *the development of techniques that deliver discoveries, predictions, recommendations, and insights based on data*. Data science technologies support the extraction of meaningful knowledge from large datasets (van der Aalst 2014) in a context in which data is constantly expanding (Xiang et al. 2015), and has been applied in marketing (Murray, Agard, and Barajas 2018; Tan, Steinbach, and Kumar 2006), product design (Köksal, Batmaz, and Testik 2011), ethnography (Weibel et al. 2013) and customer journey mapping (Bernard and Andritsos 2017).

Although the data science literature is abundant and provides useful insights, it is fragmented over various areas (Cao 2017; e.g. process mining and natural language), making it difficult for non-experts to obtain an overview of the opportunities it provides (D'Ignazio 2017). Currently, the literature fails to address how data science can support service designers. Despite the growing interest in the field (Grimes et al. 2018), data science remains inaccessible to most designers, who, due to their lack of knowledge about the topic (Götzen et al. 2018), are unable to see the opportunities and best matches for their projects.

Therefore, data science still has unfulfilled potential in supporting Service Design. To address this limitation, this paper explores *how to enable Service Design (practitioners) to adopt data science technologies* by: (1) investigating service designers' processes and needs; (2) mapping relevant data science methods for Service Design; and (3) introducing overview of data science methods for service designers. As a result, this research is valuable for both Service Design practitioners and researchers who are looking for ways to introduce methods augmented with data science into their practice or interested in expanding their current methodologies, as well as to design educators who are looking to introduce the topic to students.

In the next section, the methods and research processes are presented. This is followed by a literature review of Service Design and Data Science, which set the stage for a discussion on the challenges and opportunities at the intersection between the two disciplines. The data science methods for Service Design are then described, and next key findings from the research are discussed. The paper concludes by addressing some limitations and suggesting topics for further research.

Research method

This paper builds on a practice-based design research approach (Saikaly 2005), in which knowledge is produced in and through practice (Gibbons et al. 1994). Over successive cycles of design iteration and reflection (Crouch and Pearce 2012), *the researchers explored how to structure and communicate data science knowledge for and from a service designers' perspective*. Throughout these cycles of actions and reflection (Schön 1984), new ways to enable data science technologies to support Service Design were shaped and reflected on. This process allowed researchers to expand their understanding of the topic, facilitating the production of a framework that helps service designers become better acquainted with data science.

The design practice that informed this research was executed in a consulting context, in cooperation with a full-service digital design agency in Northern Europe. This collaboration ensured access to design projects, and also provided a structure that facilitated an engaging exchange of ideas and constructive feedback. The research went through three main phases: exploration, ideation and evaluation (Figure 1). Due to the methodological choice (i.e. practice-based design research), the research process resembles a typical design process. Yet, unlike in design practice, our focus was not on the artefacts generated by the design interventions, but on the knowledge emerging from the process (Fallman 2007).

The first phase (*exploration*) focused on exploring theoretical and tacit knowledge about Service Design and data science. The academic literature

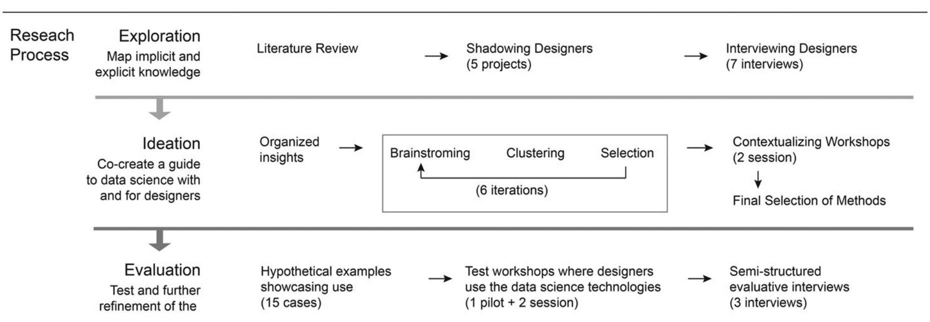

Figure 1. Detailed research process.

on Service Design and data science provided a foundation. This theoretical basis was complemented by empirical incursions in the field – namely, shadowing and interviewing – to extend the comprehension of service designers' ways of working. This investigation allowed us to identify designers' needs, guiding a further literature review of those data science technologies specifically relevant to service designers.

During the second phase (*ideation*), a *guide to data science concepts for service designers* was created and evaluated through an iterative process in cooperation with design practitioners; starting with insights from the previous phase, advancing through individual brainstorming sessions. The brainstorming sessions focused on understanding designers' perspectives, data science capabilities and on linking the two. This resulted in a list of Service Design methods augmented with data science, which were organized using paper cards – over six brainstorming rounds, cards were added and removed. The ensuing methods were then subject to a round of in-depth discussions with designers who helped to contextualize the use of the methods augmented with data science in their practice over two separate feedback sessions of 60 and 100 minutes. This led to the selection of the methods most relevant to Service Design from the designers' perspective.

In the third phase (*evaluation*), the previously selected methods augmented with data science went through an assessment round through individual critique workshops. In preparation for these sessions, hypothetical exemplary cases were developed to explain the application of the methods. The goal was to present the data science technologies from the outcome point of view – that is, instead of showing how to apply, the focus was on how designers could use the insight provided by these methods in their design projects. Three workshop sessions – a pilot (one designer), and two full sessions (two designers each) – were conducted. Following the workshops, three semi-structured interviews were conducted to discuss the overall outcome and future direction for the study.

Throughout these phases the research expanded the comprehension of *how data science technologies can be incorporated in Service Design projects from the designers' point of view*. This led to a greater understanding of the opportunities and limitations for the application of data science technologies and methods in Service Design. Later in this paper, the opportunities and challenges for the use of data science in Service Design will be further discussed.

Service design

Service Design is "an approach to designing services that balances the needs of the customer with the needs of the business" (Stickdorn et al. 2018, 20;

see also Kimbell [2011]). It represents “the application of design as a creative and culturally informed approach to services” (Clatworthy 2013, 16); that is, the use of designerly ways of working (Cross 1982) in the development and improvement of new and existing services (Segelström 2013). Service Design offers a unique perspective on service innovation and on the development of the value co-creating interactions between a business and its customers (Costa, Patrício, and Morelli 2018; Patrício, Gustafsson, and Fisk 2018).

Service Design models the social, material and relational elements that support the customer experience (Wetter-Edman et al. 2014; Zomerdijk and Voss 2010), integrating the various silos of the organization into an orchestrated service offering (Kimbell 2009); it applies human-centered and collaborative methods to explore the experience of different stakeholders. This capability of integrating several perspectives allows Service Design to develop solutions that are relevant for the customers while considering the structural context of the organization (Miettinen 2016; Stickdorn et al. 2018).

To understand the stakeholders’ experiences, service designers often borrow methods from quantitative, and especially qualitative research (Merriam and Tisdell 2015). Interviewing, observation and document analysis methods are commonly used to support Service Design research. These insights are often combined with specific tools such as customer journey maps, service blueprints and stakeholder maps (Stickdorn and Schneider 2010; Stickdorn et al. 2018), to support a holistic view of the stakeholders’ experiences with the service. Since services are rather abstract objects, Service Design tools also help to materialize the activities and processes that shape the service provision, facilitating the co-design of new solutions and offerings.

The Service Design process is both iterative and non-linear, and is, in many aspects, similar to the double diamond proposed by the UK Design Council (Yu 2017), going through rounds of divergent and convergent thinking. Service designers begin framing the problem (Cross 2010) by first developing an *understanding* of the current situation and then *defining* the design problem. Once the problem is better understood, designers focus on ideating and *developing* solutions; a concept is then chosen and advanced to be *’delivered’* for implementation (Yu 2017). It is also relevant to notice that although sometimes represented as circular, the different stages of the Service Design process are in fact iterated according to the project’s needs (Stickdorn et al. 2018).

In this paper, a model based on the double diamond model is adapted to match the processes observed in the empirical research. The resulting framework is better suited to describe the possible application of data science in Service Design. The proposed design process (see Figure 2) adds a preliminary phase in which designers ‘*prepare*’ for the project, deciding which direction it will take. A testing-specific phase is also added – highlighting the

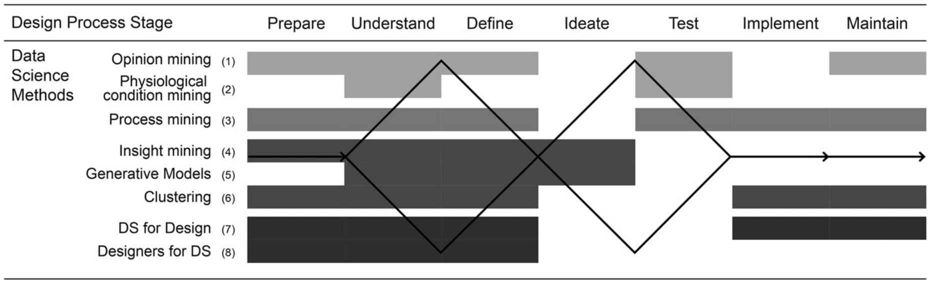

Figure 2. Relation between Service Design process and Service Design methods augmented with Data Science (based on Kunneman [2019]).

iterative nature of Service (Yu 2017) – before the *'implement'* stage, which, together with '*maintain',* helps ensure that the new (data-enabled) solutions are not only realized, but that they also are sustainable and continuously supported (Knight et al. 2020).

Data science

Customer data is a valuable resource, pointing to possible routes for the development of competitive advantage (Witten and Frank 2005). Data science, as a research field, embodies the fundamental principles that support the extraction of knowledge from data (Provost and Fawcett 2013); it provides methodologies and contextualizing tools (e.g. visualisation; van der Aalst 2014), enabling the discovering and account of meaningful patterns in large amounts of tabular data (Tan, Steinbach, and Kumar 2006; Witten and Frank 2005) or data logs (van der Aalst 2014).

In this paper, data science is seen as a source of various technologies that can provide useful insights for designers (discoveries, predictions, recommendations, insights) through the extraction of meaningful patterns and models from data (tabular, text, process logs, etc.; Cao 2017).

The application of data science technologies in the extraction of relevant information begins with determining the goal, followed by data selection, its pre-processing, the application of the technique and finally the evaluation. The result is - hopefully - new knowledge and insights (Hui and Jha 2000). However, the quality of the techniques' output is highly dependent on the data quality and its structure, which makes both high quality data selection and pre-processing steps vital (van der Aalst 2014). Therefore, identifying a technique that always works is infeasible; failure caused by poor data quality can be confused with faulty techniques, adding a new layer of complexity. The produced output also depends on the technology applied; it can be a textual statement, a visualization, association, or other type of structure

(Witten and Frank 2005). Ultimately, the results must be evaluated in relation to their accuracy and precision.

Data science technologies are generally of two types: (1) *supervised*, which learns from examples to predict for new instances; and (2) *unsupervised*, which detects new patterns or groupings without predefining any particular structure. An example of an *unsupervised* problem is cluster analysis, which divides instances into categories without knowing those categories beforehand; say, splitting a group of customers based on their distinguishing features.

Examples of supervised technologies are classification, association analysis and regression. Classification techniques focus on assigning predefined categories to instances; say, filtering some email into a spam box. Association analysis aims to find association rules in the dataset; think of the correlation between beer and diapers purchasing (Tan, Steinbach, and Kumar 2006). Regression techniques estimate the relationship between the input data and some numerical value, such as the link between sunlight in the office and sickness absence.

Service design and data science

The limited academic literature describes the use of data science techniques in design and marketing applications; for example, latent product features are automatically discovered (Köksal, Batmaz, and Testik 2011; Tuarob and Tucker 2015) or an individual customer's demand is forecast in marketing (Murray, Agard, and Barajas 2018). However, despite attention from business (e.g., Wettersten and Malmgren [2018] and Chhabra and Williams [2019]), the challenges and opportunities for data science in design are far from exhausted (Prendiville, Gwilt, and Mitchell 2018). Therefore, this section discusses the opportunities and challenges of using data science to support Service Design.

Opportunities

The main contribution of data science to Service Design is that it provides a new dimension of information, exposing patterns in data through taking a quantitative approach. Designers use a variety of research methods to support and inform their processes (Costa, Patrício, and Morelli 2018). Such methods are often taken from qualitative methodologies (Stickdorn and Schneider 2010), and help designers understand the users' context and experience. This exploration phase is central to any design process, and the use of a range of methods is essential to enable a holistic view of the situation, since it enables data triangulation, mitigating blind spots in the research process, thus improving the reliability and validity of the findings (Creswell et al. 2003).

Table 1. Data Science maturity stages – proposed model adapted from Corsten and Prick (2019).

Stage	*Description*
Explore	This first stage is about evaluating data science techniques and kick-starting the initiative. At this point, finding enthusiasts to support the initiative is essential.
Prove	The second stage, the value for business should be evident, and the foundations for the use of new methods within the organization laid.
Scale	Next, the capabilities spread beyond the initial team of enthusiasts through the organization. This can be fostered by running multiple parallel projects.
Integrate	This stage systematically integrates the methodology in the way of working of the organization. New ways of working might emerge as a consequence.
Thrive	Ultimately, the methodology becomes ingrained into the company culture and advances the state-of-the-art.

In this context, data science can provide new and increasingly advanced approaches to support the service designer's methodology toolbox. Data science techniques are quantitative and can be used in combination with qualitative methods; for example, quantitative methods can be used to validate qualitative insights and, conversely, a qualitative approach can support further exploration of quantitative findings. Moreover, data science techniques 'think' and 'learn' in inherently different ways than those designers are trained in. This way of reasoning produces significantly different conclusions, thus providing alternative perspectives. Data science also enables the prediction and/or identification of meaningful small signals and patterns from large amounts of data.

Finally, further opportunities are expected to emerge from the interaction between designers and data scientists. Throughout a project, designers immerse themselves in the problem situation, becoming – to some degree – domain experts. This knowledge can help data scientists with the extraction of more meaningful relationships from the data (Xiang et al. 2015). "Designers' ability to envision human understanding and knowledge … can lead to new intelligent algorithms and systems, in which designer and artificial intelligence work on par in more efficient and creative design processes" (Koch 2017, 418). That is, designers can help put data into context, making it more comprehensible, and thereby facilitating the development of value propositions, while considering the perspective of various stakeholders (Prendiville, Gwilt, and Mitchell 2018).

Challenges

The effective integration of data science into the design approach of an organization is a complex task. Understanding the maturity level of the organization can help recognize the challenges that will emerge, informing future decisions and facilitating the adoption of new techniques and processes. An adaptation of Corsten and Prick (2019) maturity model (Table 1) is used to describe the various phases an organization might go through to support the full integration of data science.

Building on the five stages shown above, the present research identified three types of challenges. In the early stages (Explore and Prove), (1) *technical challenges* relate to a lack of available data, inadequate data quality or restricted data access. The acquisition of adequate datasets can be a challenge, and also might reveal (un)conscious biases in both collection and selection (Merriam and Tisdell 2015). Data availability might be restricted due to cost and lack of permissions, and data quality can be compromised by poor processing, such as when duplicates are not removed or compensated for. In that context, data quality refers to the technical condition of the data.

Once resources have become available, technical capabilities are required. Especially in the Scale stage, challenges related to the need for expanding data science (2) *capabilities* beyond the original team are likely to emerge; the adoption of new and more complex techniques may well demand novel capabilities. Bringing new quantitative skills to the team can be addressed by acquiring new members or through training. Different techniques might require different levels of capabilities; therefore, the organization might also need to acquire experienced data scientists.

Finally, it is important that the value of the advancing data science capabilities is emphasized throughout all stages. Yet (3) *determining business value* presents a challenge since on many occasions value creation depends on individual projects. Furthermore, costs are highly dependent on the data sources, techniques and design context. As a consequence, the value of data science for a project cannot be guaranteed beforehand.

Service design methods augmented with data science

Through applying a practice-based design research approach (Saikaly 2005), this paper describes how to enable service designers to adopt data science technologies in their projects. Eight methods were selected for their relevance and usability: they had a clear purpose, were aligned with the designers' process and were technically feasible. These methods were then organized into four categories: user research, process analysis, serendipity and collaboration. Opportunities for the application of data science emerged throughout the entire Service Design process (e.g. generative models in the ideate phase and opinion mining in the test phase), and not only during the understand phase, as might be expected. Figure 2 shows the relation between the various methods and the stages of the Service Design process. Below, the categories and methods are introduced and explained.

User research

Designers need information. Understanding users' behaviors, feelings and emotions is a vital part of the research process that informs any design process. However, often insights might be hidden as the data requires too much processing, or their signals are too weak to be detected. Data science technologies can help make these hidden insights or patterns visible, improving the scope of the insights on which designers build their projects.

1. *Opinion Mining* – User-generated content provides a rich field for design research. Opinion mining, also known as sentiment analysis, focuses on extracting and analyzing users' responses to an event or experience (Balazs and Velásquez 2016; Poria, Cambria, and Gelbukh 2016). This technology can help designers learn about users' satisfaction levels by, for example, classifying responses as positive or negative. Another option is to correlate the extracted comments to ratings through factor analysis. Xiang et al. (2015) used this approach to understand what factors (words) related to positive reviews. This can help designers identify and prioritize the characteristics that most influence the consumer perception.
2. *Physiological condition mining* – With the help of physiological measurements, a wealth of subconscious information about humans can be extracted and analyzed. The use of electroencephalography (EEC) and magnetic resonance imaging (MRI) has helped to create a whole new field in the marketing research literature (see, e.g., Morin [2011]). Physiological condition mining technologies train models to decode users' signals; the techniques first learn from a dataset, and then predict responses from new data collected from users. This data can be from EEC and MRI, but also from more readily accessible means, such as audio and video; for example, a webcam can be used for eye tracking to measure attention. Another example is from Weibel et al. (2013) who used multiple Microsoft Kinects to analyze the communication between physician and patient, and Zhou et al. (2017) used radio frequency identification (RFID) to detect customer actions while shopping for clothes.

Process analysis

The data science technology of 'process mining' can help designers explore and evaluate data from a specific project, providing an overview of the existing processes. Data from event logs can be analyzed to extract insights and build an explicit model of the process (van der Aalst 2011). Through this technology, data science can help not only understand, but also design new processes.

3. *Process Mining* – The modelling of existing and actual processes to help extract insights about, for example, the customer experience across the service journey (Harbich et al. 2017). Comparing the actual journey with the expected (or intended) one can help prioritize actions, and lead to ideas on how to improve the overall customer experience. For example, Harbich et al. (2017) extracted individual journeys from event logs to understand citizens' routine activities across Chicago. Furthermore, they could detect deviations from and alternative journeys to the most likely representative journey, helping designers understand and respond to deviations from the expected in the users' process.

Serendipity

The discovery of new patterns enabled by data science can help designers more often achieve a moment of serendipity. The analytical nature of applying data science technologies differs significantly from designers' creative thinking processes. This provides the creative designer with a new route to discovering novel solutions. Materials from the design project can be used as input to machine generated artefacts – for example, various drawings can be combined into a new computer-generated illustration. The goal is to discover relevant information while not necessarily looking for it. These serendipitous moments can spark changes in action, interpretation and perception of the overall situation (de Melo 2018).

4. *Insight Mining* – Many design methodologies create and collect materials, artefacts, deliverables, and insights about the design project. Data science technologies can help explore and prepare these insights created throughout design projects by predicting what will be relevant. This can serve as inspiration, helping save designers from their equivalent to 'writers' block', fostering the exchange of ideas and practices across the design teams, and helping prevent the 'reinvention of the wheel'. In that context, the technologies can, as well as to improve exploration, analyze large sets of data to detect undiscovered patterns.
5. *Generative Models* – The goal is not to replace designers, but to provide tools to arrive at alternative views. These data science techniques can generate design artefacts based on existing work, for example previous projects. This can help designers develop 'quick and dirty' (alternative) prototypes and simulations. For example, Siering (2017) discusses the use of wireframe sketches to create HTML code for digital interaction. Even

user testing can be improved through the use of generative models; Cornia et al. (2018) presented a tool to simulate eye-tracking, predicting where human gaze will focus.

6. *Clustering* – As previously mentioned, data science technologies 'think' differently to designers. In that sense, the value of segmentation executed by machines lies not only on the segments they find, but also on the ways in which the clusters are formed. Model-generated segments do not build on existing labels and categories, and therefore, have the potential to discover entirely new segments, deviating from traditional marketing approaches to segmentation. For example, Agard, Morency, and Trépanier (2006), while analyzing data from Canadian public transportation, noticed that traditional age-based segments were not the best way to understand passengers' behaviors; clustering passengers by their travel patterns could lead to better design solutions.

Collaboration

The final category takes a closer look at the opportunities for the explicit collaboration between data scientists and designers. Approaches to collaboration emerged throughout this research in the same way as the other method categories; however, these approaches are not methods *per se*. The goal of this research is to explore methods that apply data science technologies; yet due to the relevance of the opportunities for collaboration between designers and data scientists, this section was included.

7. *Data Scientists for Design* – Design projects often rely on multidisciplinary teams to facilitate the development of complex solutions. In that context, designers can partner with data scientists to further explore the data. For example, data scientists can help designers validate assumptions about customers; this can be part of an ongoing collaboration or *ad-hoc*. Yet the greater the involvement of the data scientist in the project, the better. This collaboration is particularly relevant when the task is complex and indeed is essential in any of the previously mentioned methods.
8. *Designers for Data Science* – Conversely, designers can support data scientists to put insights into context, generating expanded domain-knowledge that helps to make better sense of results (Koch 2017). By combining their expertise, data scientists and designers can make more effective use of data science in the creation of value for stakeholders.

Discussion

This paper has discussed how data science can support Service Design, discussing the challenges and opportunities, and introducing eight practical methods for integrating the disciplines. In doing so, the paper explored how to link the fields from the designers' perspective, providing an entry-level guide to introduce data science technologies to service designers, helping them expand their methods toolkit. The four main findings are set below.

Integrating data science requires organizational maturity

The integration of data science into Service Design projects depends on the team's structure, the organization's structure, and the clients' (data science) maturity. Assimilating data science technologies into Service Design will increase the skills set of the project team, but this also means that these new expert skills must be acquired. Service designers must not necessarily become data science experts themselves, as new members can be brought into the team. What matters is that the service designers know what data science can offer, and that the organization builds the capacity to support its implementation. The organization must thus be capable of incorporating these skills in their processes; the maturity level will influence which challenges and opportunities the project can address. The client's maturity also affects the opportunities for integrating data science in design projects, as access to data resources often depends on the client's data access and is paramount to a successful outcome. The challenges faced in acquiring adequate data must not be underestimated.

Data science techniques can increase the breadth and validity of the user research, enabling triangulation of data

Data science can increase the breadth and validity of user research, supporting triangulation of the findings. Design teams must be critical about their research data, ensuring that the insights are unbiased. One way of mitigating against possible blind spots is to explore the data from various perspectives. In that sense, additional methods and the differing ways in which machines 'think' can help design teams develop a better understanding of the user context.

Data science can help uncover hidden information, leading to previously inaccessible insights

Data science can help uncover insights from vast amounts of data that would otherwise be unattainable for humans or would be too costly. Moreover, computers can be trained for specialized tasks, detecting signals that are often indiscernible to humans. These otherwise inaccessible insights are essential to improve the quality of user research and to enable data triangulation (as discussed above).

Data science can help designers "think out of the box", providing relevant inspiration and alternative point of views

Data science can go beyond alternative perspectives to user research, by also proposing various options through generative design, helping make the design process both more efficient and more creative. Inspiration can emerge from augmented exploration or by analyzing insights and deliverables from design projects.

Conclusion

Throughout this research, it was noticed that designers still feel more comfortable with qualitative-like insights. For example, during the workshops, designers preferred the qualitative generative models that captured the experience of the users over quantitative and demographic data. This can be attributed to the inherent nature of design research, but also shows designers' typical lack of experience in leveraging quantitative data. Yet the results show the potential of data science to support Service Design, enabling designers to expand their methodology toolbox, and encourage organizations to improve their data science capabilities to help support design projects. Service Design can benefit from these developments because it enables richer insights about users, stakeholders and applications.

With new challenges, new opportunities emerge for practitioners and researchers in data science to explore ways to improve design projects. Through a practice-based design research approach (Saikaly 2005), the most relevant data science technologies for Service Design were captured, selected and presented in this paper, which is intended as an introductory guide to data science for service designers. The research builds on both academic knowledge and practice, and was developed in collaboration with designers. This collaboration with practitioners enabled validation from the designers' perspective and ensured a focus on their needs.

As shown in Figure 2, the methods augmented with data science can be applied in various stages of the design process, and not only the early exploratory research, as would be expected. Data science can support user research, providing a range of perspectives, collecting data more efficiently, leading to new insights, sharing ideas across design teams, facilitating conversation and even prompting alternative solutions. Data science thus shows great potential to transform not only design research but the Service Design process as a whole.

The opportunities brought by data science do not come without a cost; ensuring that the organization (and its clients) are sufficiently capable and mature to implement the correct methods in their design process is essential to ensure the best outcomes. In that sense, the degree to which the opportunities can be exploited depend on the organizations' capabilities and its access to relevant data. Finally, it is important that the design teams strive to make the case for data science capabilities throughout the design process to ensure support and resources. As previously argued, demonstrating the value of the approach can be critical.

Limitations and future research

This paper has presented a list of methods compiled through an exploratory, practice-based design research; consequently, it is acknowledged that the presented list is not comprehensive. However, to our knowledge no other research has yet been published on the intersection of these topics, and therefore this paper serves a first step into the integration of data science technologies in Service Design. Moreover, due to the fragmentation of the literature and the emerging nature of the research, multiple references to non-academic sources are made. However, that is thus justified by the novelty of the topic.

The methods presented in this paper were evaluated with the help of design practitioners from one partner that works mainly in digital design. Future research might benefit from considering a more diverse mix of stakeholders and a broader audience. Data science can help in all stages of the design process (Figure 2); as novel methods emerge, the opportunities will keep expanding.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Notes on contributors

Kunneman has a background that combines Design with Artificial Intelligence (AI). She has a M.Sc. in Industrial Design Engineering from the University of Twente, and currently works as a product owner in the customer feedback market.

Motta-Filho holds a Ph.D. in Service Design from the Oslo School of Architecture and Design. He currently is an assistant professor at the University of Twente, where he links marketing to design through his lectures, and researches the use of design in a business context.

van der Waa is a research scientist at TNO and a PhD candidate at TU Delft. He uses his expertise in AI and Machine Learning to aid professionals in complex and high-risk environments. At TU Delft his research focuses on how AI can generate explanations that are meaningful for professionals and the overall task.

References

Agard, B., C. Morency, and M. Trépanier. 2006. “Mining Public Transport User Be- Haviour from Smart Card Data.” *IFAC Proceedings Volumes* 39 (3): 399–404. doi:10.3182/20060517-3-FR-2903.00211.

Balazs, J. A., and J. D. Velásquez. 2016. "Opinion Mining and Information Fusion: A Survey." *Information Fusion* 27: 95–110.

Bernard, G., and P. Andritsos. 2017. "A Process Mining Based Model for Customer Journey Mapping." In Forum and Doctoral Consortium Papers Presented at the 29th International Conference on Advanced Information Systems Engineering, 1848, 49–56.

Cao, L. 2017. "Data Science: A Comprehensive Overview." *ACM Computing Surveys (CSUR)* 50 (3): 1–42.

Chhabra, A., and S. Williams. 2019. "Fusing Data and Design to Supercharge Innovation—in Products and Processes." *McKinsey Analytics*, April 4. https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/fusing-data-and-design-to-supercharge-innovation-in-products-and-processes

Clatworthy, S. 2013. "Design Support at the Front End of the New Service Development (NSD) Process: The Role of Touch-Points and Service Personality in Supporting Team Work and Innovation Processes." PhD diss., Oslo School of Architecture and Design.

Cornia, M., L. Baraldi, G. Serra, and R. Cucchiara. 2018. "Predicting Human Eye Fixations via an LSTM-Based Saliency Attentive Model." *IEEE Transactions on Image Processing* 27 (10): 5142–5154. doi:10.1109/TIP.2018.2851672.

Corsten, N., and J. Prick. 2019. "The Service Design Maturity Model." *Touchpoint* 10 (3): 72–77.

Costa, N., L. Patrício, and N. Morelli. 2018. "A Designerly-Way of Conducting Qualitative Research in Design Studies." In *Service Design Proof of Concept. Proceedings of the ServDes.2018 Conference*, edited by A. Meroni, A. M. O. Medina, and B. Villari, 164–176. Linköpings: Linköping University Electronic Press.

Creswell, J. W., V. L. Plano Clark, M. L. Gutmann, and W. E. Hanson. 2003. "Advanced Mixed Methods Research Designs." In *Handbook of Mixed Methods in Social and Behavioral Research*, edited by A. Tashakkori, and C. Teddlie, 209–240. Thousand Oaks: Sage Publications.

Cross, N. 1982. "Designerly Ways of Knowing." *Design Studies* 3 (4): 221–227. doi:10.1016/0142-694X(82)90040-0.

Cross, N. 1999. "Design Research: A Disciplined Conversation." *Design Issues* 15 (2): 5–10. doi:10.2307/1511837.

Cross, N. 2010. "Design Thinking as a Form of Intelligence." In Proceedings of the 8th Design Thinking Research Symposium (DTRS8), edited by K. Dorst, S. Stewart, I. Staudinger, B. Paton, and A. Dong, 99–105. Sydney: DAB documents.

Crouch, C., and J. Pearce. 2012. *Doing Research in Design*. London: Berg.

D'Ignazio, C. 2017. "Creative Data Literacy: Bridging the Gap between the Data-Haves and Data-Have Nots." *Information Design Journal* 23 (1): 6–18.

de Melo, R. M. C. 2018. "On Serendipity in the Digital Medium: Towards a Frame- Work for Valuable Unpredictabilitty in Interaction Design." Unpublished PhD diss., University of Porto.

Dribbisch, K., M. Großmann, M. Jordan, and O. Scupin. 2013. "Opening the Black Box of Research." *Touchpoint* 5 (1): 20–25.

Fallman, D. 2007. "Why Research-Oriented Design Isn't Design-Oriented Research: On the Tensions between Design and Research in an Implicit Design Discipline." *Knowledge, Technology & Policy* 20 (3): 193–200. doi:10.1007/s12130-007-9022-8.

Gibbons, M., C. Limoges, H. Nowotny, S. Schwartzman, P. Scott, and M. Trow. 1994. *The New Production of Knowledge: The Dynamics of Science and Research in Contemporary Societies*. London: Sage.

Götzen, A. D., P. Kun, L. Simeone, and N. Morelli. 2018. "Making Sense of Data in a Service Design Education." *In ServDes.2018. Service Design Proof of Concept*, edited by A. Meroni, A. M. O. Medina, and B. Villari, 177–188. Linköping: Linköping University Electronic Press.

Grimes, J., A. Fineman, B. Gillespie, A. Atvur, and B. Mager. 2018. "Designing the Future." *Touchpoint* 10 (2): 88–93.

Harbich, M., G. Bernard, P. Berkes, B. Garbinato, and P. Andritsos. 2017. "Discovering Customer Journey Maps Using a Mixture of Markov Models." In *Proceedings of the 7th International Symposium on Data-Driven Process Discovery and Analysis*, edited by P. Ceravolo, M. v. Keulen, and K. Stoffel, 3–7. Neuchatel, Switzerland. ceur-ws.org.

Hui, S. C., and G. Jha. 2000. "Data Mining for Customer Service Support." *Information & Management* 38 (1): 1–13. doi:10.1016/S0378-7206(00)00051-3.

Kimbell, L. 2009. "The Turn to Service Design." In *Design and Creativity: Policy, Management and Practice*, edited by E. Julier, and L. Moor, 157–173. Oxford: Berg.

Kimbell, L. 2011. "Designing for Service as One Way of Designing Services." *International Journal of Design* 5 (2): 41–52.

Knight, J., E. Ross, C. Gibbons, and T. McEwan. 2020. "Unlocking Service Flow—Fast and Frugal Digital Healthcare Design." In *Design of Assistive Technology for Ageing Populations*, edited by A. Woodcock, L. Moody, D. McDonagh, A. Jain, and L. C. Jain, 171–187. Cham: Springer.

Koch, J. 2017. "Design Implications for Designing with a Collaborative AI." In *AAAI 2017*. Palo Alto, CA, USA: Spring Symposium Series.

Köksal, G., İ. Batmaz, and M. C. Testik. 2011. "A Review of Data Mining Applications for Quality Improvement in Manufacturing Industry." *Expert Systems with Applications* 38 (10): 13448–13467. doi:10.1016/j.eswa.2011.04.063.

Kunneman, Y. 2019. "Data Science for Service Design: An Exploration of the Opportunities, Challenges and Methods for Data Mining to Support the Service Design Process." MSc thesis., University of Twente.

Manzini, E. 2009. "Service Design in the Age of Networks and Sustainability." In *Designing Services with Innovative Methods*, edited by S. Miettinen, and M. Koivisto, 44–59. Helsinki: Taik Publications.

Merriam, S. B., and E. J. Tisdell. 2015. *Qualitative Research: A Guide to Design and Implementation*. San Francisco: Jossey-Bass.

Miettinen, S. 2016. "Introduction to Industrial Service Design: what is Industrial Service Design?" In *An Introduction to Industrial Service Design*, edited by S. Miettinen, 3–14. Abingdon: Routledge.

Morin, C. 2011. "Neuromarketing: The New Science of Consumer Behavior." *Society* 48 (2): 131–135. doi:10.1007/s12115-010-9408-1.

Murray, P. W., B. Agard, and M. A. Barajas. 2018. "Forecast of Individual Customer's Demand from a Large and Noisy Dataset." *Computers & Industrial Engineering* 118: 33–43. doi:10.1016/j.cie.2018.02.007.

Ostrum, A. L., D. Iacobucci, and F. N. Morgan. 1995. "Services Branding." In *Kellogg on Branding*, edited by A. M. Tybout, and T. Calkin, 186–200. Hoboken: Willey and Sons.

Patrício, L., A. Gustafsson, and R. Fisk. 2018. "Upframing Service Design and Innovation for Research Impact." *Journal of Service Research* 21 (1): 3–16. doi:10.1177/1094670517746780.

Patrício, L., R. P. Fisk, J. Falcão e Cunha, and L. Constantine. 2011. "Multilevel Service Design: From Customer Value Constellation to Service Experience Blueprinting." *Journal of Service Research* 14 (2): 180–200. doi:10.1177/1094670511401901.

Poria, S., E. Cambria, and A. Gelbukh. 2016. "Aspect Extraction for Opinion Mining with a Deep Convolutional Neural Network." *Knowledge-Based Systems* 108: 42–49. doi:10.1016/j.knosys.2016.06.009.

Prendiville, A., I. Gwilt, and V. Mitchell. 2018. "Making Sense of Data through Service Design." in *Designing for Service*, edited by D. Sangiorgi, and A. Prendiville, 225–236. London: Bloomsbury.

Provost, F., and T. Fawcett. 2013. "Data Science and Its Relationship to Big Data and Data-Driven Decision Making." *Big Data* 1 (1): 51–59. doi:10.1089/big.2013.1508.

Saikaly, F. 2005. "Approaches to Design Research: Towards the Designerly Way." In *Sixth International Conference of the European Academy of Design (EAD06)*. Bremen: University of the Arts.

Schön, D. A. 1984. *The Reflective Practitioner: How Professionals Think in Action*. USA: Basic Books.

Segelström, F. 2013. "Stakeholder Engagement for Service Design: How Service Designers Identify and Communicate Insights." PhD diss., Linköping University.

Siering, M. 2017. "Teaching a Machine to Convert Wireframes into Code." XING Engineering, November 27. https://tech.xing.com/teaching-a-machine-to-convert-wireframes-into-code-f9333e125e61

Stickdorn, M., and J. Schneider. 2010. *This is Service Design Thinking: Basics, Tools, Cases*. Hoboken: Wiley.

Stickdorn, M., M. E. Hormess, A. Lawrence, and J. Schneider. 2018. *This is Service Design Doing: applying Service Design Thinking in the Real World*. Sebastopol: O'Reilly.

Tan, P., M. Steinbach, and V. Kumar. 2006. *Introduction to Data Mining*. Boston: Pearson Addison-Wesley.

Tuarob, S., and C. S. Tucker. 2015. "Automated Discovery of Lead Users and Latent Product Features by Mining Large Scale Social Media Networks." *Journal of Mechanical Design* 137 (7). doi:10.1115/1.4030049.

van der Aalst, W. 2011. *Process Mining: discovery, Conformance and Enhancement of Business Processes*. Heidelberg: Springer.

van der Aalst, W. 2014. "Data Scientist: The Engineer of the Future." In *Enterprise Interoperability*, vol. 7, 13–26. Cham: Springer International Publishing.

Weibel, N., C. Emmenegger, J. Lyons, R. Dixit, L. L. Hill, and Hollan, and D. J. 2013. "Interpreter-Mediated Physician-Patient Communication: opportunities for Multimodal Healthcare Interfaces." In 7th International Conference on Pervasive Computing Technologies for Healthcare and Workshops, 113–120. IEEE.

Wetter-Edman, K. 2011. "Service Design: A Conceptualization of an Emerging Practice." Licentiate." thesis., University of Gothenburg.

Wetter-Edman, K., D. Sangiorgi, B. Edvardsson, S. Holmlid, C. Grönroos, and T. Mattelmäki. 2014. "Design for Value Co-Creation: Exploring Synergies between Design for Service and Service Logic." *Service Science* 6 (2): 106–121. doi:10.1287/serv.2014.0068.

Wettersten, J., and D. Malmgren. 2018. "What Happens When Data Scientists and Designers Work Together." *Harvard Busines Review*, March 05. https://hbr.org/2018/03/what-happens-when-data-scientists-and-designers-work-together

Witten, I. H., and E. Frank. 2005. *Data Mining: Practical Machine Learning Tools and Techniques*. San Francisco: Morgan Kaufmann.

Xiang, Z., Z. Schwartz, J. H. Gerdes, Jr, and M. Uysal. 2015. "What Can Big Data and Text Analytics Tell us about Hotel Guest Experience and Satisfaction?" *International Journal of Hospitality Management* 44: 120–130. doi:10.1016/j.ijhm.2014.10.013.

Yu, E. 2017. “A Reflection on and Suggestion of Service Design Processes.” *Archives of Design Research* 30 (1): 25–38. doi:10.15187/adr.2017.02.30.1.25.

Zhou, Z., L. Shangguan, X. Zheng, L. Yang, and Y. Liu. 2017. “Design and Implementation of an RFID-Based Customer Shopping Behavior Mining System.” *IEEE/ACM Transactions on Networking* 25 (4): 2405–2418. doi:10.1109/TNET.2017.2689063.

Zomerdijk, L. G., and C. A. Voss. 2010. “Service Design for Experience-Centric Services.” *Journal of Service Research* 13 (1): 67–82. doi:10.1177/1094670509351960.