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DATA-DRIVEN SERVICE INNOVATION: A SYSTEMATIC LITERATURE REVIEW AND DEVELOPMENT OF A RESEARCH AGENDA

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Research paper

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Abstract

The potential created by ongoing developments in data and analytics permeates a multitude of research areas, such as the field of Service Innovation. In this paper, we conduct a Systematic Literature Review (SLR) to investigate the integration of data and analytics as an analytical unit into the field of Service Innovation – referred to as Data-Driven Service Innovation (DDSI). Overall, the SLR reveals three main research perspectives that span the research field of Data-Driven Service Innovation: Explorative DDSI, validative DDSI, and generative DDSI. This integrated theoretical framework describes the distinct operant roles of data analytics for Service Innovation, and thus contributes to the body of knowledge in the field of DDSI by providing three unified lenses, which researchers can use to describe and locate their existing and future research endeavors in this ample field. Building up on the insights from the SLR, a research agenda is proposed in order to trigger and guide further discussions and future research surrounding DDSI. Ultimately, this paper aims at contributing to the body of knowledge of Service Innovation in general and Data-Driven Service Innovation in particular by presenting a three-dimensional research space model structuring DDSI towards its advancement.

Keywords: Data-Driven Service Innovation, Service Innovation, Literature Review, Research Agenda.

1 Introduction

Over the past decade, it has become a popular saying that "data is the new oil", as Clive Humby, co-founder of Dunnhumby Customer Data Research, explained in 2006. This phrase may be overused, but it still shows the ubiquitous role of data and analytics in the age of digitalization. The amount of valuable machine-readable data is steadily increasing (Turner, Gantz, Reinsel and Minton, 2014). In this data-rich environment (Troilo, De Luca and Guenzi, 2017), data and analytics can be leveraged beyond mere internal process improvements (Davenport, 2013). Instead, it can be used to develop mutually beneficial long-term customer relationships (Ostrom et al., 2015; Robinson, Chan and Lau, 2016), create new or enhance existing product or service offerings (Chester Goduscheit and Faullant, 2018), and thus create a competitive advantage (Davenport, 2013). Simultaneously, developments, such as the rise of Big Data, the Internet of Things (IoT), and Cyber-Physical systems (C.-H. Lim, Kim, Heo and Kim, 2015a, 2015b), build the foundation for the emergence of data-driven ecosystems,

which are globally connected and bear the potential of impacting our everyday life (Lokshina, Durkin and Lanting, 2017).
Due to the potential that is created by new developments in data collection and processing, data and analytics permeate a multitude of research areas, such as the field of Service Innovation. In this paper we refer to Service Innovation as the "*rebundling of diverse resources that create novel resources that are beneficial (i.e., value experiencing) to some actors in a given context*" (Lusch and Nambisan, 2015, p.161). The integration of data and analytics as an analytical unit into the field of Service Innovation – referred to as Data-Driven Service Innovation (DDSI) in this paper – has gained popularity in recent years (Demirkan et al., 2015; Rizk, Bergvall-Kåreborn and Elragal, 2017; Urbinati, Bogers, Chiesa and Frattini, 2018). Thus, the number of scientific publications dealing with DDSI has steadily increased. This can also be observed in our Systematic Literature Review, in which we were able to identify 85 papers (the majority of them ranging between the years 2010 and 2018) investigating this topic. As we will show in the course of our SLR, these publications are divided into three different research streams, which are loosely related but relatively independent from each other. However, for the progress of a certain research field, it is important that previous research is presented transparently, that the individual research streams are highlighted, and their interrelationships are presented. This is particularly important for relatively young research areas such as DDSI in order to arrive at an integrated conceptualization and synthesis of representative literature on which future research efforts can build on (Torraco, 2005). So far, to the best of our knowledge, such an integrated conceptualization does not exist, which results in DDSI being terminologically fuzzy. Our SLR addresses this gap by contributing to creating a common vocabulary and structuring the terminological basis of DDSI. Thus, we intend to answer the following research question:

Which research streams and their particular research perspectives constitute the research field of Data-Driven Service Innovation (DDSI) and how can they be precisely distinguished from each other?

The remainder of this paper is structured as follows: First, we provide a brief summary of the theoretical background on Service Innovation and data analytics before a Systematic Literature Review (SLR) according to Webster and Watson (2002) and vom Brocke *et al.* (2009, 2015) is conducted to grasp and structure the field of DDSI in its breadth and depth. Subsequently, an integrated theoretical framework covering distinct research streams on the operant role of data analytics for Service Innovation is conceptually derived from literature. Finally, a structured research agenda taking into account and building up on the state of the art in the particular research streams of DDSI is proposed.

Overall, this Systematic Literature Review intends to contribute to the body of knowledge in the field of DDSI by providing an integrated theoretical framework of the operant role of data analytics for Service Innovation. This framework suggests three unified lenses on the field, which span the three-dimensional research space of DDSI. Researchers can use the conceptually derived research space to describe and locate their existing and future research endeavors in this ample field. Structured within the research space of DDSI, a research agenda for DDSI is proposed in order to trigger and guide further discussions and future research. By compiling and elaborating on this agenda, we hope to pave the way for a more thorough conceptual convergence in the field and future research breakthroughs.

2 Conceptual Background

In recent years, scientific interest in the field of Service Innovation has grown considerably (Miles, 1993; Hertog, 2000; Breidbach and Maglio, 2015). This increased interest results from a number of overlapping trends. In the B2C-sector, the rise in living standards within the industrialized countries is increasing the demand for personal services, which is driving growth in the services sector (Bryson, Daniels and Warf, 2004). In the B2B-sector, the complexity of internal and external company structures increases the need for professional coordination services. Examples for such services include supply chain management, supply chain mediation, or services related to the logistics of a company. Consequently, numerous companies in the entire business landscape have recognized services as the driving force behind their company's growth. Along with these developments, the scientific interest in how new services are developed and commercialized has also increased. Under the headings of Service Development (Cowell, 1988; Edvardsson and Olsson, 1996), Service Engineering (Bullinger, 1999; Leimeister, 2012; Beverungen, Lüttenberg and Wolf, 2018), Service Design (Lynn Shostack, 1982; Ramaswamy, 1996; Seidelin, Dittrich and Grönvall, 2017), or Service Business Modelling (Zott, Amit and Massa, 2011; Maglio and Spohrer, 2013; Zolnowski, Weiss and Bohmann, 2014; Engel, Haude and Kühl, 2016), numerous different studies have been undertaken in recent years (Metters and Marucheck, 2007; Oke, 2007; Alter, 2008; Gallouj and Savona, 2009; Dörner, Gassmann and Gebauer, 2011; Oliveira and von Hippel, 2011). All of the fields mentioned above deal with different facets of Service Innovation from different angles and individual research perspectives and thus are part of the analysis. Here, we will highlight some key features of Service Innovation as the overarching theme of this paper as well as important research streams in this area.

According to Hertog (2000), a Service Innovation can be divided into four dimensions. These dimensions comprise the service concept, the customer interface, the service delivery system, and the underlying technology. A Service Innovation can therefore be created by varying one of these four dimensions or by recombining several of them (Miles, 2008). In addition, changes in one dimension may also require changes in other dimensions. For example, the development of a new service delivery system often requires changes to the customer interface. Following this logic, Service Innovation constitutes a reconfiguration of a service system with the goal of increasing the value of the service system (Breidbach and Maglio, 2015). This goes along with the definition of Service Innovation according to Lusch and Nambisan (2015) provided in the introductory section of this paper. An important differentiation criterion between Service Innovation and other forms of innovation such as product innovation is the interactive nature of Service Innovation (Barras, 1990). Service Innovations are often the result of technological changes or changes in market conditions, which require a certain company to adjust their services to these new conditions. In addition, Service Innovation is developed in strong interaction with customers or in co-production with business partners, whose knowledge can significantly influence the developed service (Gann and Salter, 2000; Fosstenløkken, Løwendahl and Revang, 2003; Dougherty, 2004). This human-centered perspective is a necessary defining characteristic of Service Innovation, delimitating it from other innovation disciplines and taking into account that any “service depends on people, human behavior, human cognition, human emotions, and human needs” (Maglio, 2015, p. ii). Thus, Service Innovation leads to the creation of new or improved so-called human-centered service systems, which require the development of service-specific methods and theories (Maglio, Kwan and Spohrer, 2015). Another feature of Service Innovation is that it is often based on the use of Information and Communication Technologies (ICT) (Barras, 1986). In traditional approaches to Service Innovation, ICT has only been seen as a means of providing a service that can increase the productivity and efficiency of a new service (Barras, 1990). In contrast to that, more recent work attributes a different role to ICT and views ICT as an independent resource in Service Innovation, which becomes a fundamental and transformative factor (Vargo and Lusch, 2004; Vargo and Lusch, 2008; Vargo, Maglio and Akaka, 2008; Lusch and Vargo, 2014). Based on this recent understanding of Service Innovation, it is assumed that the digitization of information, and thus the ability to collect, process and use data, will become a key success factor of Service Innovation (Yoo, Henfridsson and Lyytinen, 2010). In their study investigating the data-driven nature of modern service delivery enabled by data and analytics, Lim and Maglio (2018) use a text mining approach to define the term smart service system as “a service system that controls things for the users based on the technology resources for sensing, connected network, context-aware computing, and wireless communications” (C. Lim and Maglio, 2018, p. 166). Lim and Maglio (2018) pursue an outcome-oriented, customer-facing approach on investigating DDSI towards smart service systems, while other researchers use DDSI to analyze and improve development processes, whereas the outcome can also be a physical, non-digital service. Following this logic, data and analytics are no longer merely an operand resource that enables Service Innovation but constitute active, operant resources with the ability to initiate, guide, and therefore “drive” Service Innovation (Lusch and Nambisan, 2015). This combination of data analytics and Service Innovation into one unit of analysis is also a logical consequence from the development of the service-dominant logic (Vargo and Lusch, 2004) and the associated concept of value-in-use (Vargo and Lusch, 2008), according to which the pure analysis of data without further usage does not represent any significant value. Taking a broader view, this logic led to the development of the research field "Data-Driven Service Innovation" (DDSI), which focuses on the use of data and analytics within the whole process of Service Innovation (Demirkan et al., 2015; Urbinati et al., 2018). Although numerous studies have already been conducted within this field of research, the different roles of data and analytics in Service Innovation have not been precisely conceptualized in an integrative and holistic manner (Rizk et al., 2017). A structured systematization of the distinct perspectives and research streams of DDSI shall help to provide terminological clarity and conciseness in the field of DDSI: Within this paper, we want to address this research gap with the help of a Systematic Literature Review (SLR).

3 Methodology

A Systematic Literature Review is carried out according to Webster and Watson (2002) and vom Brocke *et al.* (2009, 2015). The overall search scope of the conducted SLR can be defined along the dimensions of process, source, coverage, and techniques of the SLR (vom Brocke et al., 2015): We use a *sequential search process* using four databases covering a wide range of business, innovation, and Information Systems (IS) literature as a *source* for our SLR. Even though the process is sequential, small iterations concerning relevant keywords are applied in order to base the literature search and analysis on a sufficient and relevant keyword set. The literature search intends to reach a *representative coverage* of the distinct perspectives on the research field of DDSI. Thus, a *comprehensive set of search techniques* – keyword search, backward search, and forward search – is used to provide the foundation for the literature analysis and conceptualization.

3.1 Paper Selection Process

Reaching reproducibility and transparency is a key quality criterion of adequately conducted SLRs. Intending to live up to these quality criteria, the paper selection process applied in this work is presented in this sub chapter. It consists of four sequential steps as depicted in *Figure 1*.

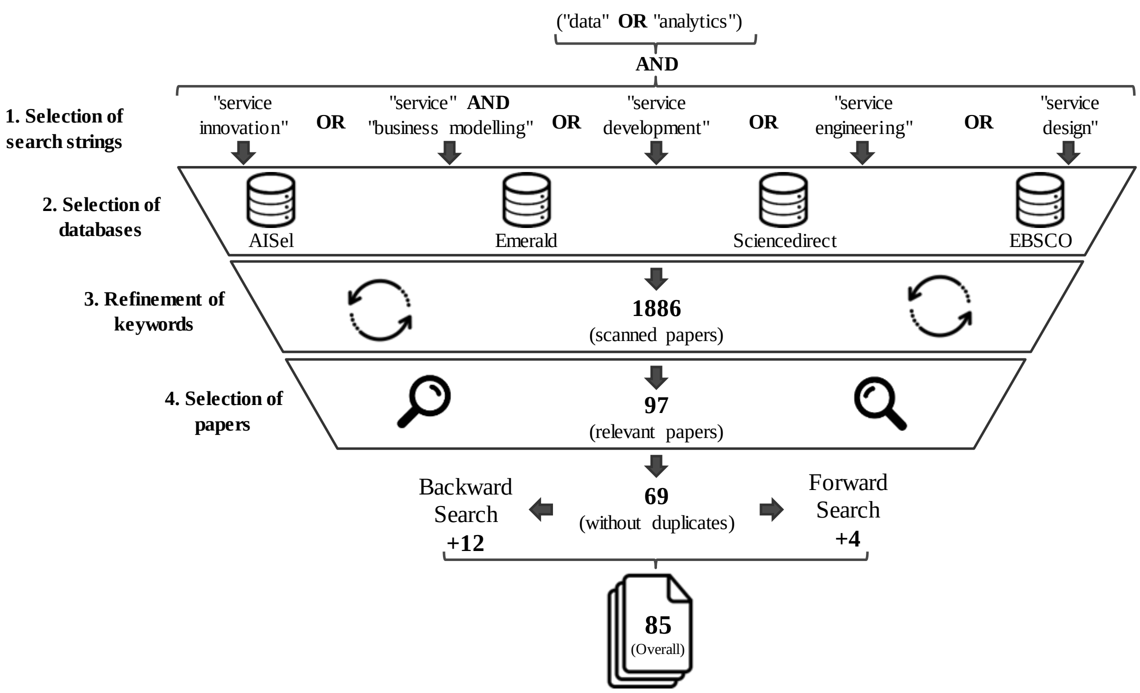

Figure 1. Four-step process of the Systematic Literature Review (SLR)

The four sequential steps of the paper selection process are explained in further detail here:

Step 1 - Selection of search strings: Aiming at covering a wide part of literature in the field of DDSI, the search strings are chosen to be broad. Thus, initially, the search string ("data" OR "analytics") AND "service innovation" is used to approach the topic area of interest. All variations of the keywords – singular, plural, hyphenated, or not hyphenated – are used in the SLR. Although the paper selection process applied here is in general sequential, as no new iteration is started after the overall number of relevant papers is determined, the set of search strings is refined iteratively (see also step 3) towards the final set of search strings (see *Table 1*). We assume that papers relevant to this research use the keywords "data" or "analytics" and "service innovation" in close proximity to each other in the text. Furthermore, we intend to find papers, which treat DDSI and its related concepts as their focus. Therefore, the database search is conducted in the title, abstract, and keywords of the papers.
Step 2 - Selection of databases: As we set the goal to identify representative literature samples of different research perspectives on DDSI, a database search covering multiple journals and conference proceedings is chosen over a purely journal-based search. We choose a database search since the horizon of possible research perspectives should not be limited upfront when trying to integratively and holistically cover a topic area. Additionally, journal acceptance processes take substantially longer than conference proceedings to be processed, which would lead to neglecting some of the most recent research. We try to avoid this as we assume that DDSI is a young and emerging topic. Therefore, four literature databases covering a wide range of business, innovation, and Information Systems (IS) literature are selected to reach a representative search coverage, in particular AISel, Emerald, Sciencedirect, and EBSCO.
Step 3 - Refinement of search strings: After iteratively refining the keywords in the course of the search process, overall, five search strings are used for searching the four selected databases. Building up on the initial search string ("data" OR "analytics") AND "service innovation", we include related concepts of Service Innovation as additional search strings to secure the integrational and holistic perspective of the SLR. Thus, we add ("data" OR "analytics") AND "service" AND "business modelling", as service business modelling is needed to instantiate successfully conducted Service Innovation endeavors. We are also interested in the concrete process steps that lead to Service Innovation to investigate how data and analytics are integrated there. Therefore, we include ("data" OR "analytics") AND "service development", ("data" OR "analytics") AND "service engineering" and ("data" OR "analytics") AND "service design" into our set of search strings. Searching in the title, abstract, and keywords of the papers, the database search reveals 1,886 hits. This number still contains duplicates and literature not relevant to the paper.
Step 4 - Selection of papers: In an initial screening process, the literature is scanned regarding title, abstract, keywords, and research domain. Only literature in the English language is included. This leads to 133 search results, which are screened in further detail. A subsequent full-text screening of the gathered literature results in 97 relevant hits. In order to be considered relevant, a particular paper had to deal with the interrelation of both data analytics and service innovation as the central focus concept and unit of analysis of the papers. Papers dealing with it in a trivial or marginal way were removed from the sample. After removing all duplicates, 69 papers remain to be relevant results of the keyword search. This leads to a relevance ratio of approximately 5.14 percent (=69/1886) and a duplicate ratio of 28.9 percent (= (97-69)/97). To enable scholars to reproduce the keyword search, *Table 1* depicts the total and relevant search results per database and search string.

	Databases*							
	AISel		Emerald		Sciencedirect		EBSCO	
Search Strings	Hits	Relevant	Hits	Relevant	Hits	Relevant	Hits	Relevant
("data" OR "analytics") AND "service innovation"	49	13	88	3	113	8	221	12
("data" OR "analytics") AND "service" AND "business modelling"	71	18	44	1	265	5	209	3
("data" OR "analytics") AND "service development"	14	3	77	1	143	8	136	4
("data" OR "analytics") AND "service design"	16	5	125	2	170	4	98	3
("data" OR "analytics") AND "service engineering"	6	1	1	0	28	2	12	1
Sum per Database	156	40	335	7	719	27	676	23
Total number of relevant literature selected from **1886** screened papers	With Duplicates:		97	+	**4** Forward Search		=	**85**
	Without Duplicates:		**69**		**12** Backward Search			

*The database search was conducted in the *title, abstract and keywords* of the papers.

Table 1. Literature search results per database and search string

The set of search techniques applied here according to Webster and Watson (2002) and vom Brocke *et al.* (2009, 2015) aims at being comprehensive. Thus, backward search and forward search are applied in addition to the keyword search. This leads to twelve additional papers resulting from the backward search and four additional papers resulting from the forward search. Overall, 85 papers are taken into account for further analysis and conceptualization.

3.2 Paper Analysis and Conceptualization

The 85 relevant papers are analyzed from a concept-centric perspective. Thus, a concept matrix is created from the literature search results (Webster and Watson, 2002) and all papers are analyzed in order to derive the distinct research perspectives on DDSI, which holistically cover the unit of analysis in an integrative manner. For this purpose, the concept matrix considers the focus concept of the article, the particular unit of analysis, theoretical and practical contributions, and the research method that was applied by the authors. Subsequently, the different concepts in literature are analytically aggregated in the concept matrix to reveal the central research streams and perspectives on DDSI in literature. The process of analysis is iterative. This means that distinct research perspectives and sub perspectives on DDSI are gathered and then merged into particular meta-perspectives, which form individual concepts of the concept matrix. This approach is based on the suggestions regarding Qualitative Content Analysis through applying the coding strategies according to Forman and Damschroder (2007). The process steps were iteratively validated by discussions between two researchers. This cross-validation approach intends to provide stable, valid, and reproducible research results. Nevertheless, it must be noted that deriving concepts from literature is always an endeavor requiring individual and intellectual human judgement. Therefore, a subjective bias can never be fully eliminated.

4 Results of the SLR on Data-Driven Service Innovation

Figure 3 depicts the number of publications over time that were identified in using our five search strings. As it is shown, the youngest paper is from 2018 and the oldest paper from 2010. There is a steep increase in publications over time, which supports our initial assumption of DDSI being an emerging research field.

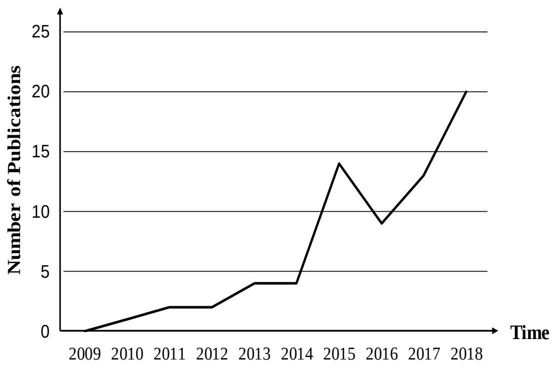

Figure 3. Timeline of publications

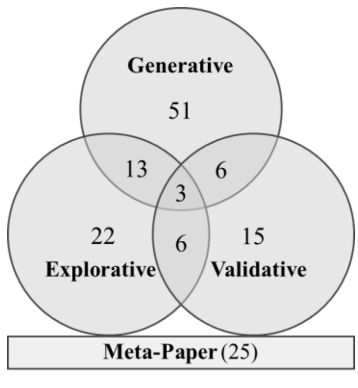

Figure 2. Numerical overlap of the DDSI research streams

Overall, the SLR revealed three main research perspectives, which span the multidimensional research field of DDSI: *Explorative DDSI, validative DDSI, and generative DDSI.* We could clearly identify most papers as belonging to the *generative DDSI* dimension (51), followed by the *explorative* (22) and the *validative* (15) dimensions. We also found a subset of papers (25) on a meta-level that elaborate on reasons for a more detailed investigation of the role of data and analytics in Service Innovation research and its theoretical foundations, which supports the rationale of conducting this SLR.

As some papers take more than one research perspective on the role of data and analytics in Service Innovation, a Venn diagram is chosen to visualize this overlap. Thus, *Figure 2* shows how many papers are aggregated in the distinct DDSI perspectives and how they overlap from a numerical point of view. In order to allow a robust categorization of existing literature, it is necessary to strive for a clear definition and description of the different research perspectives (Suddaby, 2010). Thus, we provide the particular definitions and conceptual boundaries of the derived research streams as well as the relations between them in *Table 2* according to the concept of construct clarity in order to achieve a clear delimitation between and inherent coherence within the streams (Suddaby, 2010).

	Definition	**Conceptual Boundaries**
Explorative DDSI	*Explorative DDSI* refers to the use of data and analytics for discovering opportunities, such as needs, trends, or ideas, for new or advanced services or (product-)service systems of any kind.	*Explorative DDSI* has an intraorganizational scope. It starts with the search for ideas until a final set of formulated ideas (*opportunities*) is created. Idea evaluation and service development are not in the scope of this DDSI dimension.
Validative DDSI	*Validative DDSI* comprises the guidance of the service development processes with data- and analytics-driven software tools with the goal to monitor the success and stepwise process achievements towards final Service Innovation.	*Validative DDSI* has an intraorganizational scope. It starts with evaluating and selecting ideas and ends when the *development* phase of the service is finished and the final service is about to be rolled out to the market.
Generative DDSI	*Generative DDSI* focuses on data as a key resource for value proposition to the customer during the actual service delivery.	*Generative DDSI* has an extraorganizational, customer-facing scope. Thus, the analytical focus is put on the service *outcome*. It takes place at the time of service delivery.

Table 2. Definitions and conceptual boundaries of the three dimensions of DDSI

In the following sub sections, the particular dimensions of DDSI are explained in further detail.

4.1 Explorative DDSI

We refer to *explorative DDSI* as the use of data and analytics for discovering opportunities, such as needs, trends, ideas, or design options, for new or advanced services or (product-)service systems of any kind. From a process perspective, this can be viewed as data and analytics being the trigger of the Service Innovation process, which goes along with the view of them being operant digital resources (Lusch and Nambisan, 2015). Thus, the service outcome in the explorative DDSI stream does not necessarily rely on data as its key resource for value proposition. Traditionally, the task of exploration for the purpose of Service Innovation has been approached from a quite manual perspective. Possible exploration methods include empathetic design, lead user methods, living labs (Edvardsson, Kristensson, Magnusson and Sundström, 2012), as well as interviews, or vignette studies (Ostern, Eßer and Buxmann, 2018). Ostern, Eßer and Buxmann (2018) used a vignette study design, which is rooted in psychology and sociology methods, to explore the needs related to privacy concerns when designing smart car applications, thus taking a quite traditional approach to explore how to design modern data- and analytics-driven service ecosystems. As the capabilities of applying advanced data analytics are increasingly growing, the explorative research stream of DDSI deals with leveraging data and analytics to make use of the ubiquitous data sources. This aims at making the exploration phase more efficient and effective and enabling explorations which were simply not possible before the rise of Information and Communications Technology and digitalization as a socio-technical phenomenon (Urbinati et al., 2018; Zheng, Lin, Chen and Xu, 2018). Research in this stream therefore calls for more data-driven exploration approaches such as data-driven service design tools, which integrate data as “malleable material” into Service Innovation endeavors (Seidelin et al., 2017, p. 27). To illustrate the explorative DDSI dimension, some representative examples from research identified in the SLR are provided here.

One sub stream in literature on explorative DDSI deals with the use of user-generated big data (Trabucchi, Buganza, Dell’Era and Pellizzoni, 2018). Malsbender *et al.* (2013), Lee and Lee (2015) and Tanev, Liotta and Kleismantas (2015) point out the possibilities, which the application of text mining on online data, such as sentiment analysis in social media, provides for companies when trying to identify global trends from which new service opportunities can be deducted. Similarly, Heinonen and Medberg (2018) emphasize the operant role that data-driven netnographic research can play for exploring new opportunities in Service Innovation. For instance, the authors underline that, besides delivering more personalized experiences and higher quality services, which would refer to the generative dimension of DDSI (see also section 4.3), new perspectives on traditional services can be gained, and thus opportunities for new services can be explored. This, finally, leads to fostering Service Innovation in service firms (Heinonen and Medberg, 2018). A closer look at using data mining techniques for identifying customer needs for future Service Innovation is taken by Kuehl, Scheurenbrand and Satzger (2016) and Okazaki *et al.* (2015). What Kuehl, Scheurenbrand and Satzger (2016) call "Needmining" refers to making use of Twitter data to concertedly identify tweets that contain customer needs, serving as a starting point for exploration towards Service Innovation. As this information is accessible at zero or low cost, this poses an attractive possibility to extend the set of data-driven design tools (Kuehl et al., 2016). By training an algorithm with 300 tweets about their case partner IKEA, Okazaki et al. (2015) applied a data mining model on 4000 tweets to investigate the patterns of what they call "electronic word of mouth" (Okazaki *et al.*, 2015, p. 419) to directly reflect customer needs. One step further, in the area of ideation, Chae (2015) applies descriptive analytics and content analytics, text mining, sentiment analysis, and network analytics on over 22,000 supply chain tweets to enhance supply chain research in general and provides the example of Starbucks using these kinds of analytics for extracting customer ideas for new products and services.

Another sub research stream focuses on using other data sources for explorative DDSI, such as open data (Stone and Aravopoulou, 2018) and service failure statistics (Herterich, Holler, Uebernickel and Brenner, 2015). Stone and Aravopoulou (2018) conducted a case study with Transport for London (TfL) to identify new service opportunities for London`s ageing population through the analysis of Open Data. While this is kind of an open space approach, Herterich *et al.* (2015) put the focus on exploring new opportunities for Cyber-Physical Systems through learning from the failure statistics of existing operations of a manufacturing company to identify inherent system needs, and thus generate ideas for novel offerings in product-service systems.

Approaches being in a more nascent state but aiming at making exploration for Service Innovation more data-driven are Kansei Engineering (Yeh and Chen, 2018), the use of Augmented Reality (Ruvald, Frank, Johansson and Larsson, 2018), and digital twin-enabled service design (Zheng et al., 2018). All of these approaches are enabled by the rise of the Internet of Things (IoT), (Big) Data, and Cyber-Physical Systems (C.-H. Lim et al., 2015b). Yeh and Chen (2018) extend the Kansei Engineering approach by utilizing data mining with decision trees to translate user perceptions into possible design specifications. Leveraging Augmented Reality, Ruvald *et al.* (2018) investigated experiential prototyping for gathering data in order to explore how to address the specificities of future hypothetical usage scenarios in the construction industry. Similarly, Zheng *et al.* (2018) leverage the possibilities of digital technologies to make use of data-driven digital twins, which serve as the basis for applying data mining techniques in order to identify hidden patterns for service opportunity exploration.

The examples from research within the explorative stream of DDSI described above all have the goal to lay the foundation for exploring future opportunities for services or product-service-systems in a data-driven manner, which then are developed towards the final market launch. However, the outcomes of DDSI being triggered exploratively by data and analytics do not necessarily need to be so-called data- and analytics-driven services, which use data as the main resource for the final value proposition (Hartmann, Zaki, Feldmann and Neely, 2014; Engelbrecht, Gerlach, Widjaja, 2016; Hunke and Engel, 2018). Final offerings could also be innovative, non-digital services.

4.2 Validative DDSI

The identified research stream on *validative DDSI* addresses the guidance of the service development processes with data- and analytics-driven software tools with the goal to monitor the success and stepwise process achievements towards final Service Innovation. The challenge arising in the context of Service Innovation is that traditional metrics, such as revenue or profit, are zero in the fuzzy frontend of Service Innovation (Ries, 2011; Müller and Thoring, 2012). This leads to traditional models, such as cost-benefit analysis (Schumann and Narzt, 2013; Zolnowski, Anke and Gudat, 2017), and advanced mathematical modelling, such as fuzzy set theory, Choquet integrals (Tseng, Lin, Lim and Teehankee, 2015) and rough set theory (C. Lee, Lee, Seol and Park, 2012) in the course of multi-criteria decision making, facing major difficulties for validating Service Innovation efforts. Digitalization opens a wide spectrum of data-driven possibilities that enable companies to validate the likelihood of success in their single steps towards Service Innovation more efficiently but most importantly more effectively (Ruvald et al., 2018) and tailored to situations of deciding and developing at a high level of uncertainty in the system. Van Riel *et al.* (2011) stress the importance of enriching validation results with external data, which is enabled by the technical and socioeconomical advances of Information and Communications Technology. Therefore, finding adequate proxies supported by the utilization of modern data and analytics tools is approached to address this challenge in the research vein of validative DDSI. The scope of data-driven validation reaches from single service concepts (H. Lee, Kim and Park, 2010; C. Lee et al., 2012; Ruvald et al., 2018) and service proposals (Van Riel et al., 2011) to validating different options for designing service business models (Schumann and Narzt, 2013; Zolnowski et al., 2017). All of these approaches aim at controlling and guiding the development process towards a higher likelihood of successful Service Innovation. Representative examples from research in the validative stream of DDSI are presented here to deepen the understanding of this stream:

Similarly to the explorative dimension of DDSI, one sub research stream of validative DDSI focuses on the use of netnography, such as sentiment analysis, social network analysis, and Twitter analytics using data mining algorithms (Malsbender et al., 2013; Okazaki et al., 2015; Tanev et al., 2015). In distinction to the use of netnographic tools in the explorative DDSI dimension, the focus is on producing insights on how the "explored" ideas, service concepts, and business models might perform on the market in terms of, for example, brand perception (Malsbender et al., 2013) or customer engagement (Okazaki et al., 2015). Thereby these approaches intend to guide the concrete development process, which contains prototyping and testing until the market is entered with a certain business model, which finalizes the Service Innovation process.

Another sub research stream in this dimension of DDSI focuses on the use of simulations for validative DDSI: Susha, Grönlund and Janssen (2015) suggest to use Open Data sources to simulate possible startup ideas concerning their viability. Diving deeper into simulation, Wrasse, Hayka and Stark (2015) develop an agent-based simulation model to validate innovation projects for product-service systems in order to prevent them from failing in the piloting stage due to a lack of insufficient validation. They point out the advantages of agent-based simulation as already functioning with little quantitative data and having a dedicated focus on the individual system entities (Wrasse et al., 2015).

Finally, this research stream also addresses hardware-supported validative DDSI: For instance, Mobile Ethnography (Muskat, Muskat, Zehrer and Johns, 2013) and Augmented Reality (Ruvald et al., 2018) as hardware support for gathering data points on service concept testing and validation are researched in the validative dimension of DDSI. Muskat *et al.* (2013) use mobile ethnography to test Service Innovations aiming at addressing the Generation Y in the context of museum experiences. Ruvald *et al.* (2018) leverage Augmented Reality in order to investigate the interactions between human and robot by gathering data points in a scaled down model of a construction site by applying data mining techniques to drive the development of product-service systems.

Wrapping validative DDSI up: when traditional metrics are zero, the research approaches in the vein of validative DDSI presented above ultimately aim at supporting business intelligence for guiding Service Innovation endeavors towards success (Tanev et al., 2015). However, analogously to explorative DDSI, the final service developed for the customer does not necessarily need to rely on data in the service delivery phase.

4.3 Generative DDSI

While the research streams of *explorative and validative DDSI* do not necessarily incorporate a final service outcome, which relies on data for service delivery, *generative DDSI* focuses on data as a key resource for value creation directed towards the customer. For example, user-generated (big) data (Trabucchi et al., 2018) is gathered using so-called device mesh or mesh apps to predict future customer needs, and thus offer tailored experiences (Hsiao, 2018). Crowdsensing enabled by a network of smartphones can process decentralized traffic information, and thus enable traffic optimization under time, safety, and sustainability aspects (Heiskala, Jokinen and Tinnilä, 2016). Furthermore, predictive maintenance solutions based on machine operations data are offered as value-added services on top of the machines themselves (Porter and Heppelmann, 2014; Pagalday et al., 2018). These are only some examples of so-called data- and analytics-driven services. Around the core of creating customer value from data and analytics, several research streams have evolved investigating the value creation and capturing mechanisms that enable the value extraction from data (Hunke and Engel, 2018). These data- and analytics-driven offerings can be stand-alone solutions or wrapped around existing products or services (Schüritz, Seebacher, Satzger and Schwarz, 2017). Thereby, data and analytics act as generative technologies that are the key resources required for offering the service (Herterich et al., 2015; Troilo et al., 2017). Consequently, data is viewed as a key operant resource for co-creating value (Herterich, Eck and Uebernickel, 2016). A brief summary of the research veins in the generative DDSI dimension is provided here:

One sub stream of research within generative DDSI focuses on capabilities that need to be acquired and operated to provide data-based offerings. For instance, researchers have developed process frameworks (C.-H. Lim et al., 2015a), taxonomies (Püschel, Röglinger and Schlott, 2016; C. Lim et al., 2018; Rizk, Bergvall-Kåreborn and Elragal, 2018) or adapted classic tools, such as service blueprinting and personas (O’Flaherty, Pope, Thornton and Woodworth, 2013), to support capability building on a tool-level, and thus enable practitioners to design data- and analytics-driven services. Besides capabilities on a tool-level, organizational capabilities, which are needed to offer data- and analytics-driven services, are in the focus of research. For instance, Schüritz, Brand, *et al.* (2017) elaborate on how to embed analytics capabilities within organizations in a structured way by introducing the concept of analytics competency centers as well as their types and their design. Bilgeri, Wortmann and Fleisch (2017) identify organizational archetypes through 16 in-depth interviews and elaborate under which conditions which archetype is recommended for providing data-enriched offerings.

As these analytics capabilities need to be leveraged and deployed in the market to be visible to the world and to be “exploited” for commercial profit, the second sub research stream focuses on conceptualizing, distinguishing, transforming, and developing adequate business models for commercializing and monetizing value creation based on data. Researchers treat data as the key resource of business model analysis that is needed to deliver a value proposition to the customer (Kühne and Böhmann, 2018) and view business models as an enabler of DDSI (Zolnowski et al., 2017). Research is conducted on a macrolevel including, for example, identifying business model archetypes for data- and analytics-driven services (Remane, Hildebrandt, Hanelt and Kolbe, 2016; Naous, Schwarz and Legner, 2017; Schmidt, Drews and Schirmer, 2018), and, on a more detailed business model component level, such as analyzing possible revenue models for data- and analytics-driven services (Schüritz, Seebacher and Dorner, 2017).

The concept of business models is used to leverage data and analytics capabilities in their particular service ecosystems. Thus, research on generative DDSI is also conducted from an ecosystem perspective. Exemplary service ecosystem research endeavors investigate the generative role of data for service, following the Open Innovation Paradigm (Trabucchi et al., 2018), or applying a market-based view, for example, in the case of primary personal information markets (Farrelly and Chew, 2017). The ecosystem perspective on generative DDSI is also applied on the intensely discussed phenomenon of IoT as an instantiation of data-driven ecosystems (Lokshina et al., 2017). Finally, research on Open Data as part of a bigger ecosystem of public and private services and the involved actors is viewed as being a catalyzing factor for Service Innovation (Maccani, Donnellan and Helfert, 2015b, 2015a, 2017). For instance, research explores how new data- and analytics-driven services are built on the foundation of Open data to deliver public and commercial value (Kuk and Davies, 2011; Rohunen, Markkula, Heikkilä and Heikkilä, 2014; Susha et al., 2015) such as public transportation that leverages Open Data for service advancement (Stone and Aravopoulou, 2018).

5 Discussion and Development of a Research Agenda

We aim to discuss the contributions of the Systematic Literature Review in this section and provide a research agenda that is positioned in the three-dimensional research space of DDSI.

Each of the research streams – explorative, validative, and generative DDSI – identified in the SLR exists by itself but is loosely coupled to the other streams. The Venn diagram presented earlier in *Figure 2* shows the number of papers forming the particular research streams and their numerical overlap. This visualizes that a subset of the analyzed papers has been found to apply two or more of the three identified research lenses, which underlines the necessity to sharply distinguish the research streams from each other while simultaneously elaborating on their interrelations in a structured way.

By presenting the three-dimensional framework of DDSI and distinguishing its constituting dimensions, we intend to contribute to structuring the field of DDSI. This is particularly important for relatively young research areas such as DDSI in order to create an integrated conceptualization and synthesis of representative literature on which future research work can build (Torraco, 2005). The identified dimensions of DDSI can be used to visualize a possible research space of DDSI.

Figure 4 shows how researchers can position their existing and future research in the multidimensional research space of DDSI to reach a clearly distinguished and well-positioned contribution which does not lie somewhere in the “fuzzy middle” of the research space without a clearly defined research perspective on the topic of DDSI. On the other hand, for instance, this conceptualization can help researchers to conduct more effective and efficient SLRs in the field of DDSI by enabling them to clearly shape their search queries, and thus defining the search scope in a concise manner.

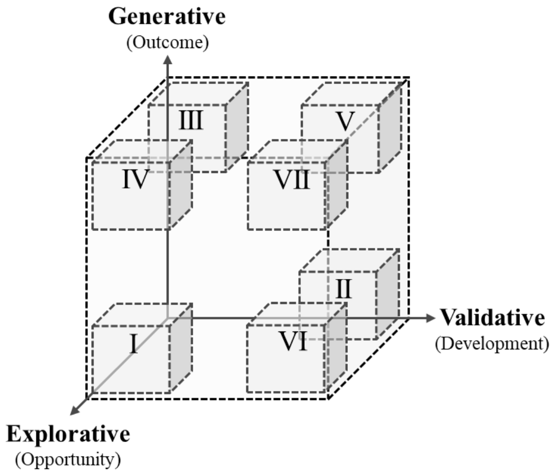

Figure 4. Research space of DDSI

In the generative DDSI dimension, data and analytics play a vital role for the actual delivery of the service. As this dimension has gained increasing popularity during the last years, some researchers might argue that this is the only dimension relevant to modern DDSI and that the other two are traditional decision support systems. We disagree with this view, as DDSI is about “driving” Service Innovation by using data and analytics. Thus, this includes integrating the Service Innovation process steps before the actual service delivery through embedding data and analytics in exploration and validation of Service Innovation endeavors. This goes along with research calls demanding a more integrated approach for driving Service Innovation (Meuris, Herzog, Bender and Sadek, 2014; Ostrom et al., 2015). Logically, this can lead to better Service Innovation outcomes, which can lead to better data-driven tools, which in turn improve the outcomes by leveraging data and analytics. This upwards spiraling effect bears immense potential, whereas a concise distinction between the dimensions is essential to foster these positive effects on Service Innovation by making use of data and analytics.

However, there is still a long road to travel in each of the identified research dimensions of DDSI and their particular hybrids. Building up on the insights gained from the SLR and the conceptualization process of the multidimensional DDSI framework, a research agenda is proposed here, aiming at triggering a fruitful discussion and further research in the field of DDSI. The single agenda points (I-VII) are structured along the possible spots in the research space of DDSI visualized in *Figure 4* but do not aim at being collectively exhaustive. Rather, this shall pose an example of how researchers can use the three-dimensional framework of explorative, validative and generative DDSI to position existing and future research on advancing services and Service Innovation in a data-driven manner:

I Explorative DDSI: Despite the advances in Information and Communications Technology (ICT), a need for enriching the set of data-driven exploration tools for Service Innovation can be observed within existing literature (Seidelin et al., 2017). Facing this research need, it should be further explored how modern technology, in the context of the Internet of Things (IoT), (Big) Data, and Cyber-Physical systems, can be used to create new data infusion channels for explorative DDSI and which organizational capabilities need to be developed to leverage them. For instance, emerging approaches being in a nascent state such as Kansei Engineering (Yeh and Chen, 2018), the use of Augmented Reality (Ruvald et al., 2018), and digital twin-enabled service design (Zheng et al., 2018) can be starting points for further research.

II Validative DDSI: Our SLR revealed that identifying adequate proxy variables in order to measure the success of the single steps towards Service Innovation is challenging and quite narrow in literature (Ries, 2011; Müller and Thoring, 2012). Eric Ries, the inventor of the lean startup approach, refers to what he calls “Innovation Accounting” in a similar manner as validative DDSI. Analogously, the challenge arising in the context of Service Innovation is that traditional metrics, such as revenue or profit, are zero in the fuzzy frontend of Service Innovation (Ries, 2011; Müller and Thoring, 2012). Therefore, future research could try to extend the set of adequate proxy variables and test their usability, for instance, by applying action research. In addition, structural guidance on how to design and implement validative DDSI in organizations should be offered by research.

III Generative DDSI: We found the value of data to be mostly operationalized through the customers’ willingness-to-pay in market-driven approaches (Farrelly and Chew, 2017). Building up on this context-driven view, it could be beneficial for theorizing on the value of data to study its underlying, static, and inherent determinants to extend the body of knowledge on the use of data as a resource in business models and its allocation in service ecosystems.

IV Generative-Explorative DDSI: The potential of so-called user-generated (big) data for Service Innovation is undoubted but research on how to approach it in a structured manner is still in a nascent stage (Trabucchi et al., 2018). Thus, the organizational and technical capabilities for closing the circle of using data for delivering and using data for exploring new (data-driven) service opportunities should be investigated and systematized in future research efforts of DDSI to bridge this gap. From a technical perspective, the necessary interface designs could be explored. Furthermore, distinct options of organizational embedment in different contexts such as the different types of analytics competency centers (Schüritz, Brand, Satzger, et al., 2017) seems to be a promising research vein.

V Generative-Validative DDSI: So far, there is very little research investigating the generative-validative intersection of DDSI. For instance, exploring analogy-based validation models based on generative DDSI sources in order to make inferences about how another (data-driven) service will perform could benefit the field of DDSI. This goes along with the idea of so-called Transfer Learning where machine learning-generated insights in one particular context are applied in other contexts or problem spaces (Pan and Yang, 2010). For instance, gathering data on the performance of one particular service in its usage environment and transferring the learnings on a service which is yet to be developed for another context could be one future research avenue in this stream.

VI Explorative-Validative DDSI: Merely exploring needs or ideas does not constitute value per se, as they need to be translated into actual innovation (Kuehl et al., 2016). At the intersection of explorative and validative DDSI, it should be identified how exploration results can be translated into development steps towards Service Innovation in a data-driven manner. For instance, combining explorative approaches such as Needmining suggested by Kuehl et al. (2016) with business model-oriented approaches such as Value Proposition Mining suggested by Augenstein, Fleig and Dellermann (2018) could help operationalize the abstract concepts of needs and ideas towards actionable insights.

VII Fully-Integrated DDSI: To the best of our knowledge, gathered in this SLR, there does not exist a fully-integrated research and process model, interlinking the data integration from early to late stages of Service Innovation, and thus pursuing a hybrid of explorative, validative, and generative DDSI. Identifying potential interfaces for connecting the dimensions and deducting required organizational capabilities and design approaches towards it could be a promising research avenue. This goes along with the service research priorities identified by Ostrom et al. (2015) where the priority of using (big) data for advancing service shows the biggest gap between its importance and the existing knowledge base in the field.

In sum, these seven emerging agenda points could serve as a first foundation for a more unified study of DDSI.

6 Limitations

Despite our attempt to rigorously analyze the identified literature on DDSI, this SLR comes with several limitations. First, the scope of the SLR is not fully exhaustive. However, we tried to encompass a broad spectrum of research on DDSI by choosing a database-oriented search over a journal-based search. This allowed us to include more recent conference proceedings as well, which is necessary when a topic is young and emerging. Furthermore, the selection of relevant papers is a process that comprises subjective judgement. Even though we tried to define and follow concise unified selection criteria to eliminate potential subjective bias as far as possible, a certain residuum always remains. We restricted the initial keyword search on title, abstract, and keywords to ensure that the search terms appear close to each other in the text, as we were interested in the interplay of data and Service Innovation as one field. Thus, the amount of information initially screened was limited, but we thoroughly analyzed the papers resulting from the initial screening in a full-text analysis using a concept matrix. Furthermore, future work building up or extending our analysis could supplement and substantiate our results by enriching them with additional bibliographic information such as citation networks investigating the loose coupling of the three research streams.

7 Conclusion

In this paper, we conducted a literature review to investigate the use of data in Service Innovation, which constitutes the field of Data-Driven Service Innovation (DDSI). Overall, the SLR revealed three main research perspectives, which span the multidimensional research field of DDSI: *Explorative DDSI, validative DDSI, and generative DDSI.* We refer to *explorative DDSI* as the use of data and analytics for discovering opportunities, such as needs, trends or ideas, for new or advanced services or product-service-systems of any kind. *Validative DDSI* comprises the guidance of the service development processes with data- and analytics-driven software tools with the goal to monitor the success and stepwise process achievements towards final Service Innovation. While *explorative and validative DDSI* do not necessarily incorporate a final service outcome which relies on data for service delivery, *generative DDSI* focuses on data as a key resource for value creation directed towards the customer. Overall, this SLR contributes to the existing literature by providing a theoretical framework of the operant role of data analytics for Service Innovation. This framework provides three unified lenses, which researchers can use to describe and locate their existing and future research endeavors in this ample field. Structured within this three-dimensional research space of DDSI, a research agenda for DDSI is proposed in order to trigger and guide further discussions and future research. By compiling and elaborating on this agenda, we hope to pave the way for a more thorough conceptual convergence in the field and future research breakthroughs.

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