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ORIGINAL PAPER

Exploring data-driven service innovation—aligning perspectives in research and practice

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Abstract
Data collected from interconnected devices offer wide-ranging opportunities for data-driven service innovation that delivers additional or new value to organizations' customers and clients. While previous studies have focused on traditional service innovation and servitization, few scholarly works have examined the influence of data on these two concepts. With the aim of deepening the understanding of data as a key resource for service innovation and overcoming challenges for a broader application, this study combines a systematic literature review and expert interviews. This study (a) synthesizes the various existing definitions of a data-driven service, (b) investigates attributes of data-driven service innovation, and (c) explores the corresponding organizational capabilities. The goal is to examine the repercussions of data utilization for service provision. The findings indicate that the use of data makes service innovation more complex. Data add new attributes, including a data-oriented culture; issues of data access, data ownership, privacy, and standardization; as well as the potential for new revenue models. The paper contributes to current discussions by providing an aligned perspective of theory and practice in data-driven service innovation and recommending that managers implement a culture and strategy that embraces the specifics of data usage.

Keywords Data-driven services · Data-driven service innovation · Servitization · Dynamic capabilities

JEL codes O32 · O33 · M15 · L86

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1 Introduction

When it comes to innovating services in the context of product-oriented organizations, service innovation (Miles 1993) and servitization (Vandermerwe and Rada 1988) are the key concepts in the management literature. The two distinct research streams (e.g., Baines et al. 2009; Baines and Lightfoot 2013; Baines et al. 2009; Kowalkowski et al. 2017) share a focus on growth based on new service offerings (Kowalkowski et al. 2017) and the creation of value through co-creative activities within networks of actors (Lusch and Nambisan 2015).

Service innovation is understood as an "*offering not previously available to the firm's customers […] that requires modifications in the sets of competences applied by service providers and/or customers*" (Ordanini and Parasuraman 2011, p. 5). Lusch and Nambisan (2015) define 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; this almost always involves a network of actors, including the beneficiary (e.g., the customer)*" (p. 161). Edvardsson and Tronvoll (2013) consider service innovation as "*a novel, better way to enable actors to […] create and/or capture value*" (p. 22). All these definitions have in common that service innovation is not achieved by a single actor but by a set of multiple actors (e.g., organizations, customers, partners, suppliers) working together within an ecosystem and co-creatively recombining resources and competences (Lusch and Nambisan 2015). Servitization, with a strong link to manufacturing, traditionally describes the "*process of creating value by adding services to products*" (Baines et al. 2009 p. 547). Providing more detail, Opresnik and Taisch (2015) outline servitization "*as a market package or bundles of customer-focused combinations of goods, services, support, self-service and knowledge*" (p. 175). Kowalkowski et al. (2017) comprehensively define servitization "*as the transformational process of shifting from a product-centric business model and logic to a service-centric approach. To varying degrees, servitization involves a redeployment and reconfiguration of a company's resource base and organizational capabilities and structures*" (p. 7). These definitions are based on the assumption that a manufacturer's competitive strategy transitions from focusing on products to providing services (Baines and Lightfoot 2013), entailing organizational change and a deepening of customer relationships (Neely 2009; Baines et al. 2009). While the emphasis on co-creative efforts and the terminology for networks and services differ, service innovation and servitization are strongly related; both highlight relationship building as well as consequent organizational changes.

The fast-changing environment of the digital era requires heterogeneous entrepreneurial organizations to co-create new service offerings rapidly. Organizations may source and develop the requisite capabilities to innovate services, in other words, to reconfigure their resources and transform their business models and structures (Teece 2018). One opportunity to innovate and disrupt is based on data; the increasing volume of data from sensors, interconnected devices, and associated analytics has the potential to facilitate the co-creation of innovative service offerings (Stein et al. 2018; Porter and Heppelmann 2014; Lusch and

Nambisan 2015). Such services utilizing data as a key resource—alone or in combination with other resources—are known as data-driven services (DDSs) (Hartmann et al. 2016).

The use of data as a resource for innovative services opens up a new area of research at the intersection between service innovation, servitization, business model development, and organizational development (Schüritz et al. 2017a, b). At this intersection, we identify a need for creating a common understanding of the required competencies and capabilities as well as the associated changes in innovation, value co-creation, and resource integration. This will be beneficial to the design of service innovation processes in fast-changing environments to advance beneficial co-creative activities and will answer the calls for research in this field. Service is considered to be a very important part of the global economy, influencing the life of almost every individual (Ostrom et al. 2015). It shifts traditional, product-centric organizations and creates a plethora of opportunities and challenges (Gebauer et al. 2021). This paper aims to identify the attributes of data-driven service innovation (DDSI) and the requisite organizational capabilities. In doing so, this article attempts to link the often abstract insights from literature with practice, aligning theoretical foundations with insights on issues in DDSI practice. It combines a systematic literature review (SLR) with a qualitative, empirical, explorative research design based on expert interviews. This methodological approach provides a unique view on DDSI that helps organizations pursue DDSI by addressing barriers through dynamic capability development. To that end, we address the following research questions:

RQ1: What defines and characterizes DDSI, and what differentiates it from non-data-driven servitization and service innovation?
RQ2: What barriers occur, and what resources, capabilities, and dynamic capabilities are required for DDSI?

This research finds that organizations must consider a variety of barriers and obtain numerous resources in order to implement DDSI. Further, it highlights how ordinary capabilities and dynamic capabilities need to be tapped or developed in an organization. These barriers, resources, and capabilities are organized in the following categories: (1) data privacy; (2) standardization; (3) data access, collection, and ownership; (4) human IT resources; (5) resource recombination; (6) revenue models; (7) external collaboration; (8) internal collaboration; (9) customer-oriented culture and strategy; and (10) data-oriented culture and strategy.

The rest of this paper is structured as follows. First, we present the theoretical background, focusing on the innovation of DDSs and the connected dynamic capabilities for digitization. Then, we describe the research approach, the SLR and expert interviews, and their analysis and synthetization. Next, we provide the findings and results, including an aligned definition of a DDS that integrates a theoretical and a practitioner's viewpoint. The subsequent discussion shows how data-related aspects add to the current understanding of service innovation. The paper contributes to the ongoing discussion on the impact of data utilization on service innovation. It depicts new aspects that should be considered during DDSI, such as data access, collection, ownership, security, privacy, and standardization, and it highlights the need for deeper collaboration among the involved actors. From a managerial perspective, the paper helps to raise decisionmakers' awareness of the increased complexity of DDSI and how the accompanying challenges can be addressed through dynamic capability development. The paper concludes with a description of avenues for further research.

2 Theoretical foundations—dynamic capabilities for service innovation in the digital age

Service innovation is multidimensional, requiring the integration of the resources, skills, and knowledge of multiple actors from an innovating organization (Lusch and Nambisan 2015). Especially in today's fast-changing environments, achieving a sustainable competitive advantage depends on more than valuable, rare, inimitable, and non-substitutable resources, as proposed by the resource-based view (Zhang and Wu 2017). In markets that change rapidly and unpredictably, creating and maintaining a competitive advantage requires integrating, developing, and reconfiguring both internal and external competences (Barney 1991; Eisenhardt and Martin 2000; Teece 1997). In particular, product-centric organizations that pursue service innovation need to transform their organizational culture, enhance customer relationships, and establish new revenue models and processes (Kindström and Kowalkowski 2014). Teece (2007) describes these dynamic capabilities as an organization's ability to (1) sense opportunities, (2) seize opportunities, and (3) manage organizational reconfiguration in order to maintain a competitive advantage. Microfoundations that specify the necessary skills, strategies, processes, procedures, disciplines, and decision rules (Teece 2007) underpin these capabilities. For successful services, these include (1) the co-creative integration of customers for innovative service provision, (2) flexible service innovation processes, (3) new revenue mechanisms, (4) the orchestration of service systems involving multiple actors, and (5) organizational transformation to establish a mental model that accommodates the particularities of a service culture. Sensing the opportunities of DDSs, seizing them, and adapting to continuous business reconfiguration is challenging, and there is still a limited understanding of the dynamic capabilities required to foster service innovation in the digital era (Coreynen et al. 2017; Ostrom et al. 2015; Barrett et al. 2015).

The impact of digitization on dynamic capabilities is a subject that is currently being discussed in the management literature (e.g., Coreynen et al. 2017; Teece 2018; Helfat and Raubitschek 2018; Canhoto et al. 2021; Linde et al. 2021). In addition to dynamic capabilities (e.g., Teece 1997, 2007), digitization requires the integration and reconfiguration of digital resources and capabilities, for example, in Big Data analytics or platforms (Teece 2018; Helfat and Raubitschek 2018). Big Data analytics capabilities, such as infrastructure flexibility, management capabilities, and personnel expertise capabilities, are key factors in organizational performance (Coreynen et al. 2017). The increasing significance of value co-creation in ecosystems and platforms (Teece 2018) demands further capabilities, including (1) innovation processes that can seize opportunities and address threats through product sequencing; (2) environmental scanning and sensing capabilities; and (3) integrative orchestration of an ecosystem, supporting value capture by the platform provider (Helfat and Raubitschek 2018).

Innovating organizations can take one of three servitization paths to accommodate digitization and the required resources, capabilities, and dynamic capabilities: (1) industrial, (2) commercial, or (3) value servitization (Coreynen et al. 2017). (1) Industrial servitization refers to the translation of internal process optimization knowledge into services that add value for customers. (2) Commercial servitization is the alignment of a service provider's value creation with the customer's internal process through novel forms of interaction (e.g., an online interface). Finally, (3) value servitization is the introduction of new digital products that renew the current value chain to impact customer processes (Coreynen et al. 2017). These three pathways require diverse resources (e.g., online interfaces, product data), capabilities (e.g., user involvement, design-to-service capabilities), and dynamic capabilities (e.g., hybrid offering sales, data processing, interpretation) (Coreynen et al. 2017).

Based on the emerging opportunities for service innovation from the collection, analysis, interpretation, and recombination of data, the aim of the present study is to clarify the attributes of DDSI and to specify the associated capabilities and dynamic capabilities that are essential. The study addresses needs for research related to the provision of services in highly uncertain environments where organizations need to reconfigure themselves and be highly flexible (e.g., Ostrom et al. 2015) to overcome challenges (Schüritz et al. 2017a, b) by developing dynamic capabilities (Teece 2018). Investigating the phenomenon from a dynamic capabilities perspective seems to be particularly fruitful.

We explore the research questions against this background. RQ1 forms the basis of this research, examining the status quo DDSI in theory and practice. RQ2 probes the (dynamic) capabilities required for the implementation of DDSI.

3 Methods

The present study takes a twofold approach to investigating the attributes of capabilities for DDSI, combining an SLR with expert interviews. The systematic review of the extensive existing literature aims to assess the influence of data on service offerings and service innovation. The interviews with industry experts, including managers and experienced practitioners involved in the innovation of DDSs, facilitate an in-depth understanding of DDSI based on the individual perspectives and personal experiences of interviewees (King and Horrocks 2010). The triangulation of an SLR and a qualitative reflection helps to increase the study's validity (Patton 2002), enriching aggregated insights from the literature with contemporary insights from innovation practice. This approach allows the past to be examined (SLR) to analyze where service innovation already took place with the use of data. It helps to gain a comprehensive overview of the academic research in this specific field. This overview is enriched by the qualitative approach that provides information on ongoing DDSI activities from a practical perspective.

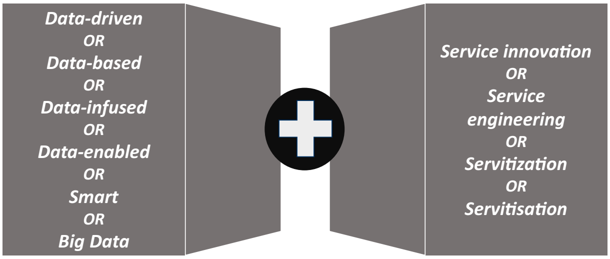


Fig. 1 Keyword combinations

3.1 Step 1: Systematic literature review

The analysis of existing scholarly articles on DDSI in the form of an SLR is based on the approach of Webster and Watson (2002). Their three-step approach entails: (1) article identification through searching scientific databases for both journal articles and conference proceedings; (2) a backward search that allows the researcher to identify articles that were cited by the literature identified in step one and should also be considered; (3) a forward search that identifies relevant articles which cite the literature selected in step one (Webster and Watson 2002).

3.1.1 Data collection

We searched the established scientific databases Scopus and Business Source Complete (EBSCO) to identify the relevant literature in the field of interest. These two are regarded as the primary databases for literature searches (Gusenbauer and Haddaway 2020), and it is very likely that the inclusion of other databases, such as Web of Science or Google Scholar, would not have yielded additional results due to the superiority of Scopus (Gusenbauer and Haddaway 2020; Mongeon and Paul-Hus 2016; Bar-Ilan 2018; Visser et al. 2020). By using both databases, this research goes beyond prior studies in this domain that relied on only one database (e.g., van Aaken and Buchner 2020; Rybnicek and Königsgruber 2019), matching those that used multiple databases (e.g., Wankmüller and Reiner 2020). Furthermore, the forward and backward searches conducted identified further important literature that was not detected by the literature search. Relevant keywords were identified and subsequently combined in search strings (see Fig. 1) based on literature screening and discussions with two expert researcher panels. As we sought to include publications on service innovation in a digital context that were as recent as possible, our search encompassed published conference proceedings (i.e., from the European Conference on Information Systems, the International Conference on Information Systems, and the Hawaii International Conference on System Sciences). In this rapidly evolving

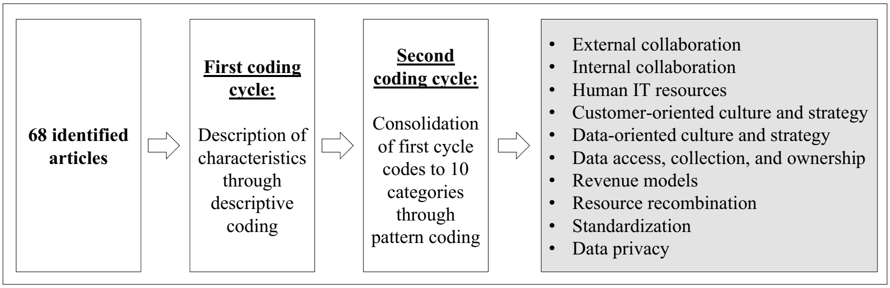


Fig. 2 Coding cycles and resulting codes for data analysis

research field, conference proceedings identified in the CORE (Computing Research and Education Association of Australasia)[1] rankings or the German Academic Association of Business Research (VHB)[2] rankings were included as recent scholarly work.

In selecting keywords and retrieving articles for the final sample, we focused on finding a strong connection to the use of data—or at least information and communication technologies—for service (innovation). We excluded articles that did not discuss the use and analysis of data for service. These publications addressed other forms of analytics or the addition of services such as predictive or preventive maintenance.

The keyword search retrieved 2.919 articles. The titles of these publications were screened to yield 398 articles. In the second step, abstract screening resulted in a total of 164 articles being chosen to be read in full. This assessment yielded 55 academic publications that were relevant from a content perspective. Building on this initial selection of articles, a thorough backward and forward search (Webster and Watson 2002) generated 13 additional academic and conference papers that were included in the final sample of 68 articles (see Appendix 1).

3.1.2 Data analysis

An abductive approach was used to capture the attributes of DDSI in a concept matrix (Webster and Watson 2002); the categories emerged during the data analysis (de Ven 2007). The literature was coded descriptively, with relevant passages summarized in short sentences or descriptive words. Descriptive coding provided an initial overview of the topics covered by the data and laid the groundwork for further coding, interpretation, and analysis (Saldaña 2016; Wolcott 1994). This first cycle resulted in 90 codes, such as "*monetary value of data*," "*outsourcing*," and "*user-centric perspective*" (see Appendix 2). In a second cycle, pattern coding was used to reduce the number of topics and sentences from the first cycle. Pattern codes are

[1] https://www.core.edu.au/conference-portal.

[2] https://vhbonline.org/en/vhb4you/vhb-jourqual/vhb-jourqual-3/complete-list.

"*explanatory or inferential codes, ones that identify an emergent theme, configuration, or explanation*" (Miles et al. 2013, p. 86), synthesizing major themes into a smaller number of similar themes with commonalities for further analysis (Miles et al. 2013; Saldaña 2016).

We subsumed codes from the first cycle that shared commonalities and assigned them to ten pattern codes to characterize DDSI (Fig. 2). For the assignment of first-cycle codes to second-cycle codes, please see Appendix 3. Appendix 4 provides an overview of the literature on DDSI and its attributes in the form of a concept matrix (Webster and Watson 2002).

3.2 Step 2: Interview study

To make sure this research connects to the logic in practice (Mohrman and Lawler III 2011) and to more deeply explore the attributes of DDSI from a practical perspective we carried out qualitative interviews with DDSI experts from central Europe between May and October 2018. Following the guideline of Creswell (2014), a purposeful selection of experts was implemented; Semi-structured interviews with a guideline were chosen as the suitable manner to explore and combine knowledge in a flexible interview style, close to a natural conversation (Miles et al. 2013).

The purposeful sampling approach aims to select participants based on their qualities. In particular, expert sampling was applied that is useful when a particular field lacks observational evidence (Etikan et al. 2016). For this research, we applied the following criteria: (a) The experts' company considers DDSs as an important element of their current strategy; (b) the experts are experienced managers working with data as a key resource for innovation, so their active involvement in the innovation of DDSs enables them to reflect on their experiences in this particular field; (c) they are accessible and willing to share information. The search for experts was implemented using reputation sampling (from participation in research projects/industry events and well-known cases) combined with snowballing (Swanborn, 2010); the final selection of experts aimed to include a variety of voices and the greatest possible variety of sectors (Myers and Newman 2007; Suri 2010); hereby, the final step of this our sampling sought to avoid contextual bias (Eloranta and Turunen 2015). Achieving sufficient data for synthesis, the expert interview study is built on ten subsequentially conducted interviews overall (Suri 2010). The selected experts represent ten organizations in the healthcare, manufacturing, and automotive sectors. All the experts work in organizations with a product-centric background that complement their portfolio with DDSs. The positions, industries, job experience, and DDS fields of the interviewed experts are depicted in Table 1.

The interview questions focused on the understanding and definition of DDSs, including the attributes and role of DDSI in their organizations. Open questions were asked first, to prevent bias from the researcher, more detailed questions later (Myers and Newman 2007). We conducted the interviews in German, either face-to-face in the interviewee's office where possible (interviews 8 and 10) or telephonically (interviews 1–7 and 9). The interviews took 33 min in average (ranging between 25 and 54 min). Combining face-to-face and telephone interviews was

Table 1 Interviewees—position and sector

Interviewee	Position	Branch	Number of employees (approx.)	Job experience	DDS Field
1	Digital Innovation Manager	Manufacturing	20.000	> 3 years	Industry 4.0
2	Digital Strategy Manager	Healthcare	100.000	> 5 years	Around-the-pill-services
3	Innovation Manager	Manufacturing	5.000	> 10 years	Predictive Maintenance
4	IT Innovation Manager	Automotive	130.000	> 5 years	Mobility Services
5	Head of R&D	Manufacturing	10.000	> 5 years	Predictive Maintenance
6	Service manager	Manufacturing	13.500	> 10 years	Predictive Maintenance
7	Digital innovation manager	Healthcare	55.000	> 10 years	Digital Ecosystem
8	Digital factory	Automotive	85.000	< 3 years	Predictive Maintenance
9	Business development and strategy	Manufacturing	60.000	> 10 years	Automation
10	Head of service	Manufacturing	300.000	> 5 years	IoT Services

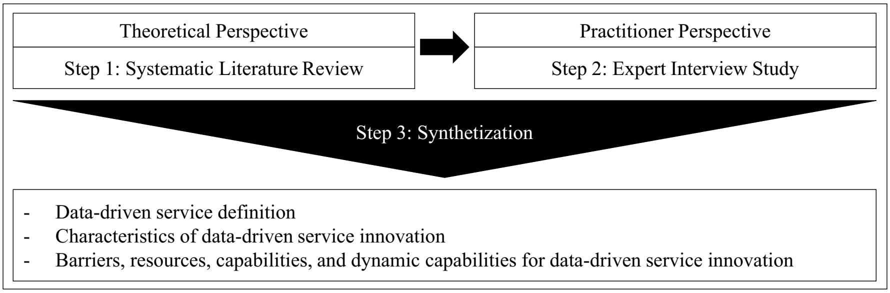


Fig. 3 Data analysis procedure

considered appropriate due to the similarities between the telephone and face-to-face semi-structured interview situations, which both allow for the collection of rich textual data of a similar type and depth for further data analysis (Sturges and Hanrahan 2004; Cachia and Millward 2011) and reduction of social distance in the usual context of the interviewee (Myers and Newman, 2007). The interviews were recorded verbatim for subsequent transcription and coding, using the qualitative data analysis software MAXQDA 12.

For data analysis purposes, we followed Gioia et al.'s (2013) approach. They propose three-steps for data analysis: a first-order analysis of terms, the second-order analysis of themes, and the aggregation of dimensions in a third step. To discuss terms, two researchers independently, assigned terms to the interviewees' statements in the first step, resulting in 31 different terms, such as "data privacy laws," "alignment capability," and "agile process capability". After discussing and aligning on this first coding, we assigned the identified terms to the attributes that emerged from the literature analysis. Here, the creation of new categories was not impeded; this means that new aspects not fitting prior ones would have been grouped in a new category. However, all relevant codes were applicable to the ten prior categories obtained from the extensive SLR. Furthermore, we analyzed how the interviewed experts defined DDSs, which served as an additional category during coding.

3.3 Step 3: Synthesis

In a third step, the findings from both the SLR and expert interviews were synthesized with the aim of deriving a definition of a DDS from a scientific and a practitioner's viewpoint. Supporting the goals of this study, the synthesis of DDSI understandings in theory and practice (Saldaña 2016) used the categories from the SLR to structure the coding of the qualitative interview data. The identified attributes were aggregated (Gioia et al. 2013) to the dynamic resource configurations described by Coreynen et al. (2017): barriers, resources, ordinary capabilities, and dynamic capabilities (see Fig. 3).

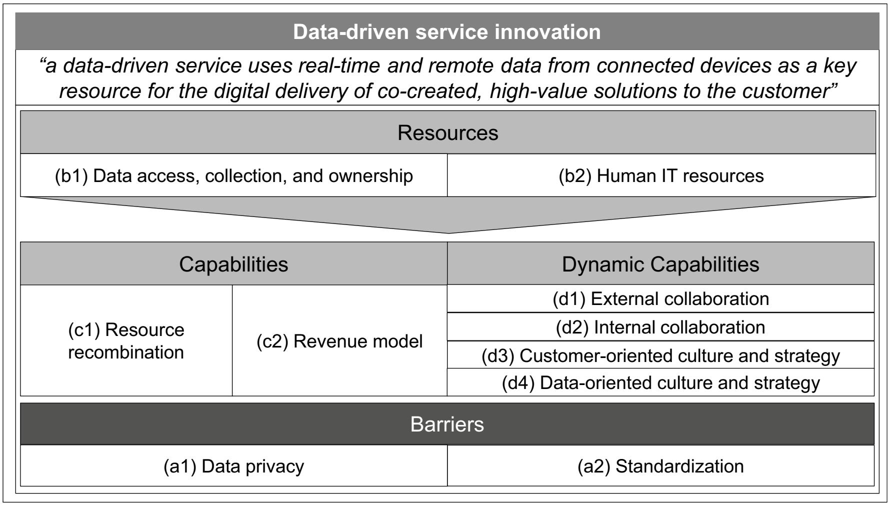


Fig. 4 Findings from the data analysis and synthesis

4 Findings and discussion

Based on the definitions and attributes of DDSs and innovation, the data analysis produced three main findings: (1) a synthesized definition of a DDS; (2) 10 attributes of DDSI; and (3) resources, capabilities, and dynamic capabilities required for DDSI (see Fig. 4).

4.1 Synthesis of data-driven service concepts

The literature analysis, combined with the findings from the expert interviews, emphasizes several elements describing and defining a DDS:

- DDSs are delivered digitally, from interconnected physical devices, potentially influencing the provider–customer relationship
- Data are a key resource in providing analytics-based services
- DDSs are provided and co-created in networks of actors
- DDSs allow for services to be provided free from the constraints of time, location, and customer involvement

Starting with the overall perception of the concept of DDSs, the SLR highlights the diversity of the terminology currently used to describe the underlying attributes of DDSI. Not all authors explicitly conceptualize the provision of services that utilize data; some of the most frequently used terms include "*digital*" and "*smart*"; these terms are used interchangeably, but can be differentiated as follows. "*Smartness*" indicates a strong dependency on information technology (IT), as well as the use of data collected remotely and in real time (e.g., Geum et al. 2015; Bullinger et al. 2015; Grubic and Peppard 2016). IT is seen as the basis for smartness (e.g., Bullinger et al. 2015; Demirkan et al. 2015; Kamp et al. 2016) as well as for the application of analytics (e.g., Anke 2018; Zheng et al. 2017; Beverungen et al. 2017).

"*Digital*" offerings/services/servitization refer to the use of IT to provide services that rely on digital components of **interconnected physical products** (e.g., Vendrell-Herrero et al. 2017; Rymaszewska et al. 2017; Lerch and Gotsch 2015). While digital systems act intelligently and without further human intervention (Lerch and Gotsch 2015), digital services are **delivered digitally** and are controlled by the customer (Immonen et al. 2016). Digital technology is used to enable fundamental changes in the dimensions of service value (Remane et al. 2017) and influences the **provider–customer relationship** (Coreynen et al., 2016).

The **key role of data** is emphasized in the reviewed publications with terms such as "*big data services*," "*data-driven services*," "*data-driven innovation*," "*data-as-a-service*," and "*datatization*" (e.g., Herterich et al. 2015; Schüritz et al. 2017a, b; Demirkan and Delen 2013). Data from **connected devices** are utilized to improve processes and to seize opportunities for innovation (e.g., Chen et al. 2016; Opresnik and Taisch 2015; Herterich et al. 2015). Data from product-service-systems or cyber-physical systems are described as a **key resource** for new DDSs co-created within **networks of diverse actors** (e.g., Herterich et al. 2015; Schüritz et al. 2017a, b; Zolnowski et al. 2016).

A few publications include services that facilitate **co-creation** of value in the discussion; this is achieved through advanced offerings that broaden manufacturers' operations (Lenka et al. 2017; Baines et al. 2009) or through value-added services that utilize data analytics to deliver product-inherent services (Nino et al. 2015; Davenport 2014). These often rely on **remote services**, such as predictive analytics (Nino et al. 2015). They **allow for services to be provided free from the constraints of time, location, and customer involvement** (Westergren 2011; Jonsson et al. 2008; Brax and Jonsson 2009).

The analysis of the interview data shows that the interviewees are aware of the existence of distinct terms describing DDSs. Interviewees remarked that this discourse is characterized by a range of 'buzzwords,' especially among customers and colleagues who lack the necessary technical or IT knowledge to precisely differentiate between concepts. The interviewees agree that even among those with theoretical knowledge, the majority of practitioners do not really differentiate between the terms used in the literature as described above. For example, Interviewee 1 states, "*I buy a service or I use a DDS not because I want to buy a Big Data service. I want to buy it because it promises to improve my production, and I don't care if it's with Big Data or with Smart Data or with whatever kind of data, as long as it solves the problem for me.*" In general, the interviewees emphasize the benefits of using data as a primary resource. As Interviewee 7 puts it, "*For me, a DDS is not only based on the collection of data, but also on the analysis, which together create added value for the customer.*"

The review of the different concepts shows that there are different foci that are addressed. While e.g. datatization refers to an ongoing digital transformation based on data, data-as-a-service mainly focuses on an interpretation of a concrete business model. The same applies to value-added or remote services. A more technological approach is expressed by definitions that emphasize the smartness or digital nature of solutions provided. However, the described concepts address a common phenomenon: the utilization of data to provide innovative service offerings with and for the customer. Even if the concrete terminology differs, they all refer to the same basis, making it fruitful to synthesize these concepts and build on the interviewees' practical insights, to propose the following definition:

> *A DDS uses real-time and remote data from connected devices as a key resource for the digital delivery of co-created, high-value solutions to the customer.*

The term *data-driven* is chosen to highlight the importance of data collection and analysis for the provision of services that would otherwise not be possible, and to avoid differing interpretations of broader terms such as *smart* or *digital*.

Data-driven service innovation barriers, capabilities, dynamic capabilities, and underlying attributes.

Analyzing the distinguishing elements of DDSI, barriers, capabilities, and dynamic capabilities during the SLR yielded 10 aspects with a couple of sub-elements. The distinguishing elements are (1) data privacy; (2) standardization; (3) data access, collection, and ownership; (4) human IT resources; (5) resource recombination; (6) revenue models; (7) external collaboration; (8) internal collaboration; (9) customer-oriented culture and strategy; and (10) data-oriented culture and strategy. Table 2 shows the 10 attributes that emerged from the coding cycles in order of frequency, along with the relevant sources, underpinning the synthesis of the collected data for further analysis and discussion.

As shown, we matched these attributes to Coreynen et al.'s (2017) resource configurations. This is important to assess the attributes of DDSI in order to explore their potential to overcome barriers and challenges as well as to identify critical (dynamic) capabilities (Coreynen et al. 2017). This means that organizations engaging in DDSI must consider data privacy issues and ensure access to the necessary data for collaboration. This implies that DDSI dynamic capabilities need to include customer relations processes and management (Story et al. 2017). It is also necessary to develop the required IT capabilities to analyze and interpret data and link them to domain knowledge. Orchestrating the service network effectively is essential to be able to transform the whole organization and gain a sustainable advantage based on innovative DDSs. In particular, integrative capabilities along the whole value chain and across different organizational units enable the transformation of governance structures to encompass the entire ecosystem of internal and external complementary asset providers. This enables value co-creation built on the use of data for service provision (Helfat and Raubitschek 2018; Teece 2018).

(a1) Data privacy

Both the analysis of the literature and the expert interviews show that data privacy issues can impede the innovation of DDSs. As a solid foundation for data use and to ensure that service providers choose legally secure locations for their data servers, the introduction or application of strict and appropriate data privacy laws

Table 2 DDSI—barriers, capabilities, dynamic capabilities, and underlying attributes (dimensions based on Coreynen et al. 2017)

Dimension	Characteristic	Findings	Findings from SLR	Finding from expert interviews
(a) Barriers	(a1) Data privacy	Data privacy laws	X	X
		Trust among partners	X	
		Personal data protection		X
		Works council interventions		X
	(a2) Standardization	Interfaces for machine-to-machine interaction	X	X
		Usage of open platforms for data exchange	X	X
		Certification		X
(b) Resources	(b1) Data access, collection and ownership	Access rights and ownership	X	X
		Data exchange within service networks	X	X
		Sharing of data in the German market		X
	(b2) Human IT resources	Ability to connect analytics and business	X	X
		Social skills for acting within the service network	X	
		Build-up of IT competencies in sales departments		X
(c) Capabilities	(c1) Resource recombination	Data-combination capability	X	X
		Meta-level application capability	X	X
	(c2) Revenue models	Outcome and performance based revenue model capability	X	X
		Pricing capability	X	X
		Long-term relationships establishment capability	X	X

Table 2 (continued)

Dimension	Characteristic	Findings	Findings from SLR	Finding from expert inter-views
(d) Dynamic Capabilities	(d1) External Collaboration	Service networks capability	X	X
		Collaboration platform capability	X	X
		Outsourcing capability	X	X
		Customer needs sensing capability		X
		Sourcing decision capability	X	
	(d2) Internal Collaboration	Distributed data source exploitation capability	X	X
		Alignment capability	X	
		Internal IT capability		X
		Interdisciplinary capability	X	X
		Agenda setting capability	X	X
		Trust capability		X
	(d3) Customer-oriented culture and strategy	Processes alignment capability	X	X
		Data exploitation capability	X	X
		Customer bargaining power management capability		X
		Customer interaction capability		X
	(d4) Data-oriented culture and strategy	Data trust capability	X	
		Corporate strategy alignment capability	X	X
		Agile process capability		X

can help to increase trust in services that make use of confidential data (Chen and Zhang 2014; Demirkan and Delen 2013). These laws should cover personal data (Demirkan et al. 2015), operational or productivity data (Kamp et al. 2016; Thoben et al. 2017), intellectual property, commercial secrets, and financial data (Chen and Zhang 2014). Failure due to data privacy issues can undermine trust among partners and the service provider's brand image, reputation, customer confidence, and revenues, especially if there is sensationalist media coverage of any breach (Demirkan et al. 2015; Demirkan and Delen 2013). As Interviewee 6 notes, the German market is considered especially sensitive to data privacy issues: *"The perceived risk in other countries is far lower than in Germany, but that doesn't mean that you don't need to pay attention to it; even if the customer doesn't care […] when it happens, he has also had bad luck."* Outsourcing certain activities for DDSI creates additional data security risks (Sanders 2016), "*because if we can read the data, theoretically someone else can, too"* (Interviewee 5). Additionally, DDSs that are based on sensor data raise the perceived potential for controlling employees, as well as know-how drain (Westergren 2011).

Failure related to data privacy problems can slow down the innovation of DDSs, for example through work councils. As Interviewee 6 put it, these councils may even "*prevent some market introductions because there's something discovered again and again. So that's an essential and influencing factor."* This dimension adds to the literature as it stresses the exchange of information and knowledge in DDSs. Service providers must take data privacy aspects seriously to enable customer adoption (Wünderlich et al. 2015). Building trust through encryption (Zissis and Lekkas 2012) and emphasizing the underlying legal framework are recommended measures.

(a2) Standardization

One distinctive attribute of DDSI emerging from our analysis is a standardized interface for data collection, use, and exchange through machine-to-machine interaction (Kamp et al. 2017). Without standardization, internal systems based on proprietary solutions may not be interoperable, impeding collaboration with other actors in the network (e.g., Demirkan et al. 2015; Grubic and Jennions 2017; Kamp et al. 2016). The use of open platforms for the standardized exchange of data can foster collaboration (Herterich et al. 2016), even internally, when departments use non-compatible systems (Wen and Zhou 2016). Standardization enables rapid information exchange across organizational borders, reducing lead times and increasing efficiency (Sanders 2016). The interviewees also see the potential of standardization to earn the trust of customers, *"who are still a bit skeptical and don't know if it's a sustainable solution that you're offering"* (Interviewee 1). The interview data show that certification could fight skepticism about this issue. Certification allows organizations to explicitly show their customers that they rely on a standardized set of rules. Adding to the literature, we find that DDS innovators require extra resources for certification activities to meet customers' demand for reliable solutions. Existing industrial standards for machine operation may be extended to innovative technologies, such as human–machine interaction, to facilitate exchange, incorporate the user, and improve processes within the network (Posada et al. 2015).

(b1) Data access, collection, and ownership

Data collection, access rights, and clarity about ownership are central issues discussed in the reviewed literature (e.g., Demirkan et al. 2015; Nino et al. 2015; Rymaszewska et al. 2017) and the interviews. Access to data can be restricted because of (a) technical issues; (b) the unwillingness of actors to share data on their problems or failures; or (c) outdated systems and irregular routines, where data download and exchange are not automated (Grubic and Peppard 2016; Grubic and Jennions 2017; Pigni et al. 2016). It is suggested that organizations need to be able to specify the essential data in advance and to ensure the exchange (including extraction and transmission) of those data (Kamp et al. 2016). Establishing information networks can ensure a continuous exchange of data between partners for DDSI (Schüritz et al. 2017a, b); here, the line between service consumers and providers is blurred, and new forms of interaction and data analysis emerge (Beverungen et al. 2017). This extends prior knowledge through the focus on appropriate infrastructure that facilitates access to and collection of network data by linking internal systems and enabling the recombination of data from different sources (Porter and Heppelmann 2014). Concerns about the regulation of data access, collection, and ownership are overcome when the customer understands the value of the DDS offered. As Interviewee 1 remarks, *"that's why it's so important to identify these problems […]. We deal with the pain for you here, and once you have the product, then you'll be really happy, but what we need […] is your data."* Interviewee 5 is *"aware of the fact that data access is currently an issue; the customer is actually also aware that this is an unregulated […] grey area. So, no terms and conditions are handed over to define exactly which data now belongs to whom, who may do what, and so on. At the moment, this is a bit experimental."* In addition, the analysis of the interview data shows that openness to data sharing differs across markets and contexts. As Interviewee 6 remarks, *"The more industrial* [the context]*, the less willingness there is to open the communication channels and do it yourself instead."* A proposed method to mitigate these issues is to consider different models of data ownership during the co-creation of services. One option is for organizations to pursue full ownership of data accruing from the provision of DDSs. This would simplify the discussion of data monetization. Alternatively, joint data ownership by the service provider and the customer (Porter and Heppelmann 2014) could align with the co-creative nature of DDSI and deepen relationships and innovation (Kowalkowski et al. 2013a, b).

(b2) Human information technology resources

The analysis reveals that for DDSI, organizations require additional employees with multiple IT skills to perform analytical work and to link those insights to business (e.g., Troilo et al. 2017; Schüritz et al. 2017a, b; Rymaszewska et al. 2017). Interviewee 2 supports this view, suggesting that this issue is *"a very big one. And those are the ones* [employees] *that are hard to find […]. The employees themselves don't have the IT knowledge that it just needs, and you just try to counter that by building digital teams that come into the projects here and support this aspect."* To connect analytics with business, employees need IT competencies and knowledge of other technical domains, such as engineering and mechatronics, as well as an understanding of the relationship between data analytics and real-world applications (e.g., Grubic and Jennions 2017; Kamp et al. 2016; Demirkan et al. 2015). As Interviewee 5 put it, *"IT knowledge is something you can buy; industry-specific expertise is more important. It is more important for me to have someone who knows how parameter A can be related to parameter B. The expertise—how I can use hypothesis testing to find out from the data whether this is really the case—I can outsource this as soon as I know what I want to test."* This indicates that some IT knowledge can be bought (i.e.. the outsourcing of IT-related tasks to other companies), while more sophisticated analyses require connecting IT knowledge with industry-specific knowledge.

Hiring IT specialists can be challenging. Issues such as employee training and skill exchange have already been addressed in the literature (e.g., Alghisi and Saccani 2015; Vargo and Lusch 2008). DDSI adds complexity by introducing special requirements for interdisciplinary knowledge in IT and engineering, linked to strong social skills to facilitate knowledge sharing across the workforce.

Organizations can offer special development courses or training to educate employees internally (Lerch and Gotsch 2015; Bullinger et al. 2015; Cenamor et al. 2017) or externally (Pigni et al. 2016). IT, technical skills, and knowledge of the business demand social skills that support the sharing of employee competences in the network (Troilo et al. 2017; Bullinger et al. 2015; Aho 2015). The findings add to the literature the proposal that IT employees should be able to act flexibly in a multi-actor environment to implement and design the required processes for DSSs (Story et al. 2017; Kamp et al. 2016; Hou and Neely 2018). The analysis of the interview data suggests that it is also crucial to train the sales department in terms of IT competencies.

(c1) Resource recombination

Both the SLR and the empirical data analysis show that combining data from different sources could improve the collection and subsequent use of data. This means that organizations need to build up their ability to reuse, repackage, and recombine service data from customers with other sources, such as product, service, or information modules, to improve or even innovate new service offerings, better meet customers' needs, and create additional value (e.g., Brown 2017; Cenamor et al. 2015; Kamp et al. 2016). New offerings can move away from the micro level (i.e., specific to a use case) to deliver insights on a more general level; the latter can be transferred to other cases and applications (Sorescu 2017) through the recombination of data, contextual business expertise, and models to generate valuable service insights (Troilo et al. 2017). Under centralized management, a service platform can allocate and recombine data from various sources to reduce waste and operational costs and accelerate service responses (Zheng et al. 2017; Yoo et al. 2012; Beverungen et al. 2017).

However, Interviewee 3 reveals skepticism about his organization's current data recombination capabilities: *"we will not really be able to transfer it because the processes are too different [...]. However, this may change in the long term. At present, the technical framework conditions to realize this are still lacking [...]. And it's* *going to take some time until the data volumes become so large or the diversification across the customer mass becomes so great that I can learn from it and offer new services."* These aspects show that DDSI opens up a variety of possibilities for the future as the amount of data grows. Data gathered from one customer can be recombined through the development of appropriate capabilities with data collected from the whole service network to deliver improved services and potentially offer novel solutions to customers (Vargo et al. 2015; Yoo et al. 2012).

(c2) Revenue models

Organizations that pursue DDSI must be able to extend traditional revenue models from product sales to outcome- or performance-based models, in which payments depend on the achievement of certain performance goals (Aho 2015; Zolnowski et al. 2017), and a service-for-free mentality predominates (Schüritz et al. 2017a, b). The price demanded for a service is related not only to historic prices paid by former customers but also to a wide range of further (unstructured) data, such as weather or competitor prices (Davenport 2014). Long-lasting service contracts increase the provider's risk of exposure to the service paradox, where significant investment in service provision fails to generate the expected high returns because of increasing costs (Gebauer et al. 2005; Neely 2009). The findings add to the service literature by showing that the monetary value of data remains unclear and lacks generalizability. These difficulties increase the complexity of pricing, especially for service providers with limited experience of new outcome-based revenue models (e.g., Hou and Neely 2018; Robinson et al. 2016; Thoben et al. 2017). Therefore, organizations are required to develop their ability to implement suitable revenue models. These rely on long-term relationships and require a certain degree of flexibility in reacting to environmental changes, with increased dependency on the customer that shifts risk away from the customer (Hou and Neely 2018; Schüritz et al. 2017a, b).

Interviewee 1 refers to a range of possible revenue models: *"So whether this is 'pay per use' or monthly subscription or 'I'll share your savings' or 'pay once and you can use it forever,' everything is possible. And the bandwidth should definitely be used, or 'pay what you want,' […]. Everything is possible, and […] this should be used much more, explored much more, and experimented with."* According to Interviewee 5, however, it can be difficult to assess a solution's benefits because of the unclear added value: *"This means that if I could assure a customer that his production productivity would increase by 1% if he gave us all his data, then he would do so […]. The thing is that the added value often cannot be clearly shown […] in the sense of an added value that I can calculate in euro."* In particular, the data analysis shows that common revenue models such as single transactions or subscriptions can be extended to multi-sided arrangements of various kinds, such as endure-ads, brokerage fees or data selling (Schüritz et al. 2017a, b).

(d1) External collaboration

The majority of the scholarly articles and expert interviews stress collaboration among diverse actors as crucial for the innovation of DDSs, in line with prior findings. Collaboration affects the integration of actors downstream (e.g., customers) and upstream (e.g., suppliers). Value is co-created within a network that integrates data from multiple sources (e.g., Belvedere et al. 2013; Opresnik and Taisch 2015; Story et al. 2017). The selection of actors and the formation of innovation alliances provide technological advantages based on existing knowledge and complementary resources. (e.g., Bigdeli et al. 2017; Davenport 2014; Grubic and Jennions 2017). Organizations can avoid possible asymmetries within the network through exploiting their competitive advantage by retaining control over elements of the offering that are hard to imitate (Vendrell-Herrero et al. 2017) and developing dynamic capabilities for external collaboration.

Collaboration with third parties enables the sensing of new opportunities and the innovation of additional DDS functionalities and features (e.g., Cenamor et al. 2017; Kowalkowski et al. 2013a, b; Lenka et al. 2017). Integrating customer and service provider processes to facilitate the joint discovery of opportunities for the co-creation of DDSs can yield additional benefits (Lenka et al. 2017; Kowalkowski et al. 2013a, b). For example, the use of open platforms for DDSs within the service network can support the development of services (Cenamor et al. 2017; Yoo et al. 2012).

External collaboration is discussed in both the literature and the interviews in terms of outsourcing non-core competencies to incorporate knowledge of data analytics-related tasks or cloud platform buildup; this allows organizations to focus on their core business while avoiding the operational risks of missing capabilities (e.g., Chen et al. 2016; Demirkan and Delen 2013; Demirkan et al. 2015). Interviewee 5 acknowledges the importance of this issue *"with certainty, because that simply requires IT knowledge or IT expertise. We have the research-specific technical knowledge, which you must integrate with IT knowledge, and that's definitely where partners are needed."* The finding that DDSI particularly focuses on new IT-related actors adds to the literature. External collaboration with IT service providers (to outsource tasks beyond an organization's perceived core competencies) or financial institutions (to set up a suitable revenue model) seems beneficial in exploiting the full potential of DDSs and leads to additional complexity.

Organizations can also take advantage of third-party providers' guaranteed service levels in terms of availability and performance, as in the case of cloud solutions (Demirkan et al. 2015). This is especially valuable for SMEs with limited resources (Lerch and Gotsch 2015). As Interviewee 3 notes, *"you will certainly have to implement more bilateral cooperation, because you can't do it on your own; not everything is in-house anymore, and we are forced to collaborate to this end."* At the same time, outsourcing can add complexity by requiring organizations to orchestrate additional actors (Chen et al. 2016).

Collaborating with experienced actors can unlock the full potential of DDSs, as in the case of new revenue models (e.g., pay-per-use). Financial institutions can help organizations design these models (Gebauer et al. 2017) or ensure the connectivity of products with sensors for data collection (Herterich et al. 2015). Organizations need to transform and establish clear roles and responsibilities for diverse actors to improve value co-creation (Grubic 2014; Immonen et al. 2016; Schüritz et al. 2017a, b). Customer collaboration is a prerequisite for data access and verification to ensure meaningful and effective innovation of DDSs (Grubic and Peppard 2016). Collaboration with partners can lead to (a) deeper and sustainable relationships (Coreynen et al. 2017; Kowalkowski et al. 2013a, b; Zolnowski et al. 2016), (b) better exploitation of the collected data (Herterich et al. 2016), and (c) better market positioning (Zolnowski et al. 2016). SMEs, in particular, should consider collaborating with external partners, as their limited human and financial resources preclude certain tasks required by their customers (Kowalkowski et al. 2013a, b), such as data analytics or cloud computing. These firms should also consider a continuous realignment of their assets (Teece 2007).

(d2) Internal collaboration

Both the literature and the interview data suggest that an organization preparing for DDSI needs to connect distributed data sources to facilitate the exchange of data from individual silos in real time and with permanent access (Demirkan and Delen 2013). In particular, centralized data analysis that provides suitable solutions for the whole organization (Troilo et al. 2017; Zheng et al. 2017) is considered beneficial. This is distinct from analysis at the point of origin, where, for instance, sufficient computing resources must be deployed (Herterich et al. 2016). Centralized data analysis can exploit dedicated data centers or new units that act independently within an organization (Schüritz et al. 2017a, b) to bypass the limitations of established structures and to act in more agile ways. In addition, centralized data analysis can provide visibility throughout the organization, bridging any gaps between IT and other units (such as marketing and sales) by integrating key actors from these functions (Aho 2015). The findings add to the literature by showing that data is a key resource for internal collaboration, as distributed data sources demand closer internal exchange to exploit the potential of DDSs.

Some organizations may encounter a lack of trust among different units and their members when attempting to foster the exchange of knowledge across functional borders. Creating interdisciplinary teams (Bullinger et al. 2015; Herterich et al. 2016; Wen and Zhou 2014) helps organizations develop trust and commitment among various units (Troilo et al. 2017), capture new value (Robinson et al. 2016), and avoid internal inconsistencies (Hou and Neely 2018; Sanders 2016) or seize opportunities from DDSI. As Interviewee 3 remarks, *"This division of labor that we currently find in many firms—where the sales department receives customer requirements and passes these on to the development department […] will no longer work. In other words, all these departments simply have to move much closer together and exchange a lot more information."* It may also be beneficial to set up centralized units for tasks such as data collection and analysis, which operate across organizational units to prevent the emergence of data silos (Gebauer et al. 2005; Parris et al. 2016).

Additionally, the interviews confirm that IT departments have to move away from being purely internal service providers to becoming solution providers for external offerings. In line with this, Interviewee 3 states that *"the IT department, which in many firms acts […]to satisfy its own concerns and needs, suddenly has to at least establish how to solve these future problems for externals."* This requires organizations to employ dynamic capabilities for continuous reconfiguration (Teece 2007).

(d3) Customer-oriented culture and strategy

The co-creative nature of DDSs requires a customer-oriented culture that enables an organization to design offerings that meet customers' specific demands and needs and satisfy these by fully exploiting the potential of the available data (e.g., Aho 2015; Grubic and Peppard 2016; Kowalkowski et al. 2013a, b). The expert interviews reveal that this interaction between the service provider and the customer may align value-creation processes (Coreynen et al. 2017), improving service quality (Demirkan and Delen 2013) and resulting in a long-lasting relationship.

Data analytics and tracking (e.g., of customer journeys or service usage) can also be used to further understand (strategic) customer needs that extend far beyond traditional paths (e.g., Davenport 2014; Demirkan et al. 2015; Gebauer et al. 2017). The use of data for service innovation can help to seize novel services and optimize existing services (Kowalkowski et al. 2013a, b; Robinson et al. 2016).

However, the interview analysis also reveals that providers using customer data face an increase in customer bargaining power. As Interviewee 7 notes, *"Customers are actually more likely to increase their role and strength, as is the case for many who want to develop innovations with the customer, whose data they need."* As customer-centricity and value co-creation with customers are among the most important features of service innovation (Baines et al. 2009; Vargo and Lusch 2008), our analysis supports that data utilization facilitates new ways of assessing customer requirements and extends current provider–customer relationships through integration with customer processes.

In networks that use data and technology for service delivery, customer needs and demands are especially dynamic as the network evolves, leading to ambiguities and changing requirements (Immonen et al. 2016). Disregarding these dynamic and diverse customer needs when innovating DDSs increases the risks of reduced customer satisfaction and glitches in service delivery (Hou and Neely 2018). This is why DDSI should originate from customer requirements (Story et al. 2017). At the same time, DDSs should leverage potentials for further utilization of the data; here, internal improvements can be a source of competitive advantage (Zolnowski et al. 2016). According to Interviewee 6, *"if I were to sum it up […] for us, this is actually the key to lifelong service at the customer's plant, with retro-fit (modernization) and the whole business—customer loyalty, yes, for the entire life cycle. That's actually what we want to achieve, and of course we now add attractive benefits for customers in the form of Big Data analysis."* As Interviewee 2 put it, *"this has consequences because you try to use the data to better understand the interaction with the customer and then adjust the services accordingly."* In this way, data both enables and demands deeper integration of actors and resources within a network that supports value co-creation (Lusch and Nambisan 2015; Schüritz et al. 2017a, b), which must be orchestrated by the service provider.

(d4) Data-oriented culture and strategy

An aspect that our analysis adds to the non-DDSI literature is the recommendation to establish a data-oriented culture for a business to capture data's value. In particular, the SLR confirms that reliable insights from data—rather than gut feelings, instincts, or intuition—could be the basis for decision making (Troilo et al. 2017; Pigni et al. 2016). Both the SLR and the interviews indicate the need for organizations to provide employees with a clear strategy for DDSs, taking into account issues such as data access and usage and relating this to the organizations' overall strategy (e.g., Schüritz et al. 2017a, b; Aho 2015; Sanders 2016). The data strategy should ensure continuous data provision and access to external data sources (Schüritz et al. 2017a, b) and should align with previous manufacturing or product–service system strategies rather than being a standalone strategy (Grubic and Peppard 2016; Opresnik and Taisch 2015). Interviewees emphasize the establishment of agile processes with short cycles. For example, Interviewee 1 makes the following observation: *"Culturally, I would say, that's another influence because, unlike physical products, a new complexity arises—not just with data-driven products but with Industry 4.0 products in general. Suddenly, hardware meets software, service, data, and so on. And to master this complexity, you need new development methods, and of course, the whole matter of agility. Scrum is a very important thing."* This means that for an organization to transition to a more service-oriented business, it must sense and seize a long-term orientation (Gebauer et al. 2005; Kindström and Kowalkowski 2014) and ensure the data-specific alignment of its services, manufacturing, and data strategy. For example, employees should be aware of the benefits of data, and the data strategy should foster co-creation and resource integration by deepening the customer orientation across all network actors.

5 Conclusion and outlook

This paper addresses two distinct questions: What defines and characterizes DDSs and their innovation, and what resources, capabilities, and dynamic capabilities are required for DDSI to overcome emerging barriers? In doing so, the paper links several concepts that center on the use of data in service provision and innovation, leading to a synthesized definition of a DDS in pursuit of a common understanding.

In light of the contemporary importance of data and the enhanced potential for collecting, analyzing, and interpreting data, the study identified ten attributes of DDSI. These were compared to non-DDSI and servitization to reveal new attributes, commonalities, and how certain aspects gain importance when data are utilized for service provision. The SLR helped us learn from the past and condense the knowledge from prior literature (Webster and Watson 2002). The qualitative research approach, entailing expert interviews, provided a perspective on current developments in this specific field. The paper shows that DDSI has certain attributes, extending the knowledge on service innovation. Organizations should focus on developing suitable strategies and a data-oriented culture. They must consider aspects such as data privacy or data security to build up the required IT competencies (or make decisions to work with other actors in this field), and introduce appropriate revenue models that differ from traditional ones. This paper also reveals that well-known rather 'soft' attributes of regular service innovation, such as customer centricity, resource recombination, and collaboration, are even more important for DDSI. Finally, the paper shows how DDSI can be seen as a pathway for organizations seeking to innovate DDSs and identifies the specific barriers, capabilities, and dynamic capabilities involved. In particular, the required dynamic capabilities in terms of strategy, culture, and collaboration shed a new light on service innovation that uses data as a key resource.

5.1 Theoretical implications

The present study extends the research on dynamic resource configurations for the delivery of additional value to customers through DDSI (Coreynen et al. 2017). While earlier approaches used information and communication technologies to enable service provision, DDSI entails additional barriers, resources, capabilities, and dynamic capabilities. For example, there are extra barriers related to sales competencies (Coreynen et al. 2017) because of the additional need for IT knowledge. Other barriers are related to data privacy laws, works council interventions, and a lack of platforms for open data exchange. Here, DDS innovators need to consider the resources needed to help employees cope with these barriers. From a capability perspective, the paper highlights the need to be able to recombine data from different sources and apply findings at the meta-level, which requires data analytics skills and the ability to link analytics to specific domain knowledge. Multi-sided revenue models add new pricing mechanisms beyond outcome-based models that rely on the solution's value-in-use (Kindström and Kowalkowski 2014). Determining this value requires additional pricing capabilities.

When transforming their business to a data-driven model, organizations can achieve a sustainable competitive advantage by managing the reconfiguration of resources and capabilities (Teece 2007). This entails deploying dynamic data-oriented change and service network capabilities and incorporating a mindset that recognizes data as a key resource for service provision. Additionally, organizations must identify and strengthen their role in the service network by integrating additional actors to capture the value of orchestrated activities (Helfat and Raubitschek 2018). To that end, top management must develop governance procedures that support sourcing decisions and responsiveness to changes in the environment, setting the organizational agenda and enabling the continuous modification of the business by showing trust in the actors involved (Teece 2007).

5.2 Managerial implications

From a managerial perspective, this paper helps to deepen the understanding of the phenomenon of DDSI. It displays attributes of DDSI that extend the ones that emerge during regular service innovation. Management should develop a suitable mindset, guiding principles, and solution space to support innovating teams' ability to work with (a) more complexity and (b) more intensive collaboration. In particular, the study has concrete implications for decision makers in terms of the aspects that should be considered during the implementation of an organizational strategy for DDSI. Challenges and barriers, such as privacy and data ownership, occur on both an intra- and an inter-organizational level. Increasing the awareness of these challenges and creating supporting structures in organizations can be strategies to overcome such barriers on the way to DDSI. It helps managers to critically review current innovation activities under the consideration DDSI specifics.

Driving and fostering the development of organizations' ordinary and dynamic capabilities may also help to overcome DDSI-related barriers and challenges. The continuous sensing of opportunities and threats from data usage (such as new technologies or regulatory issues) can help organizations identify new technical applications and changing customer needs. Seizing these opportunities has the potential to create novel possibilities for DDSI. Focusing on these activities through building up interdisciplinary or data capabilities and the support given to actors in related roles can help organizations unleash the full potential of DDSs that make the customer the focus of value co-creation.

Furthermore, the results raise the awareness of the ongoing reconfiguration of organizational strategy. The development of dynamic capabilities is necessary considering changing environments, contexts, and business models. The present study emphasizes that management should implement a culture and strategy that considers the specifics of data usage, including working in partnerships, co-creating with customers, and innovating with insecurity. The findings could be the starting point for the development of organizational routines through suitable guidelines that encompass the crucial aspects of DDSI. Additionally, organizations could pursue the implementation of tools or methods that take into account the dimensions and characteristics presented, helping firms face the specifics that come along with DDSI in contrast to regular service innovation.

5.3 Limitations

This study has some limitations. While we combined an SLR and expert interviews to ensure timely insights from broad perspectives, the individual research methods have their shortcomings. Although we tried to achieve objectivity throughout our research, the SLR was limited by the subjectivity of the initial keyword determination, the article selection criteria, and the coding procedure of the findings. The article selection process strongly relies on the subjective assessment of the literature reviewer (Tranfield et al. 2003; Kraus et al. 2020). We tried to reduce this effect by working in a team and continuously discussing the inclusion/exclusion of articles as well as the coding structure and the code assignment. Including other academic literature during the selection process could have added to the definition or the attributes. During the coding procedure, the categories evolved inductively from the data and were thus strongly influenced by the literature at hand. A connected limitation arises from the selected sample of experts for the interviews. In particular, the composition of the panel, with all interview partners from Germany, limits the generalizability of the results. Aspects such as data privacy could be overrepresented in Germany, despite the fact that they are also important in general. Meeting high data privacy-related standards would ensure a worldwide rollout of DDSs that satisfy user needs in regard to this specific aspect. Furthermore, the relatively small sample size (10 interviewees) and the different industries represented restrict the generalizability of the interview findings. Nevertheless, the interviews provide in-depth information on a rather new phenomenon and give a good cross-sector overview, indicating that even if the specific domains differ, similar challenges and attributes emerge. The self-reported nature of the interview data increases the chance of bias in the responses. However, the triangulation of different methods helps to eliminate some of the limitations through cross-data validity checks.

The generalizability of the results is also limited by the research methods used. A quantitative investigation of the identified barriers, resources, capabilities, and dynamic capabilities could show the influence of single aspects on the phenomenon. This approach could encompass many organizations pursuing DDSI and gain additional insights that support the generalizability of the findings from this study.

5.4 Future research

The findings point to some interesting opportunities for future research in the evolving field of DDSI. First, building on this study's insights and limitations, a fruitful pathway for future research is to investigate the identified attributes of DDSI in greater depth, including the effects of data use on service networks, partnerships in complex networks (Bigdeli et al. 2017), and the integration of resources from independent actors (Story et al. 2017). Other interesting research directions include the implications of DDSs for value co-creation among customers and suppliers (Grubic and Peppard 2016; Herterich et al. 2016; Lenka et al. 2017; Schüritz et al. 2017a, b), and the long-term impact of data-rich environments on the network (Troilo et al. 2017). These investigations should extend beyond the external network to include intra-organizational aspects (Schüritz et al. 2017a, b; Kamp et al. 2016). Here, additional research on actors, their roles during DDSI, and how these roles support organizational change can add to the current knowledge in this particular field.

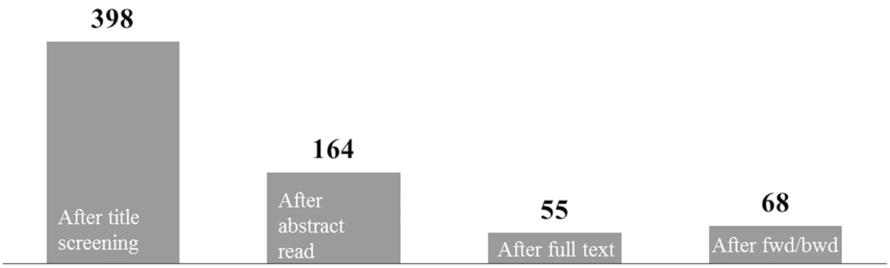
Second, additional research on the cultural and strategic changes associated with DDSI and the requisite tools and concepts for a successful transition toward a data-oriented business offers huge potential. Understanding the implications of data-rich environments would also contribute to the literature on organizational change (Kamp et al. 2016; Schüritz et al. 2017a, b) in terms of emergent opportunities and challenges (Lerch and Gotsch 2015). In particular, future research could focus on investigating and developing concrete approaches for organizations dealing with DDSI, especially formerly product-oriented organizations, which are more likely to struggle with the transition.

Third, the present study highlights the rather neglected question of data privacy and security in DDS provision (Schüritz et al. 2017a, b). Disregarding this aspect, especially in countries with a strong focus on data protection, could impede the implementation of DDSs. It would be interesting to investigate in greater detail how collaboration (e.g., with works councils) can be improved and which kinds of data most often cause privacy issues. Even if data privacy and security issues are not as important in global markets as in European countries such as Germany (Müller and Voigt 2018), meeting high standards in this regard will allow organizations to roll out their service offerings worldwide. Thus, researching these aspects will deliver benefits on a local and a global basis and allow the innovation of DDSs with different data privacy and security levels.

Finally, as the value of data and assessing this value remain poorly understood, undermining the delivery of DDSs, it would be useful for future research to explore models and tools that can help organizations develop applicable revenue models (Schüritz et al. 2017a, b) and pricing strategies (Vendrell-Herrero et al. 2017). It would also be worthwhile to investigate the risks faced by inexperienced organizations in long-term contracts, especially when these are outcome-based (Hou and Neely 2018

Appendices

Appendix 1: Article selection procedure



Appendix 2: Overview on codes after first coding cycle

- Agile processes
- Analytical capabilities
- Automated data exchange
- Big data expertise
- Business model reconfiguration
- Centralized vs. decentralized data analytics
- CEO involvement
- Co-creation
- Co-creation in value networks
- Co-innovation
- Combination of products & services
- Continuous data exchange
- Control of knowledge
- Control of skills
- Cooperative productivity improvement
- Cooperative value innovation
- Creation of analytics departments
- Cultural change
- Customer integration
- Customer needs
- Customer requirements
- Customer satisfaction
- Customer-centric value innovation
- Customer-oriented attitude
- Data access
- Data culture
- Data exchange
- Data interpretation capabilities
- Data monetization
- Data ownership
- Data possession
- Data privacy & security
- Data processing capabilities
- Data provision by customers
- Data security
- Data silo integration
- Data-driven mindset
- Data-oriented culture
- Decentralized structures
- Design of new revenue models
- Digital platform
- Digitalization capabilities
- Downstream collaboration
- Ecosystem setup
- Employee training
- Explicit strategy
- External collaboration
- Innovation of cooperation
- Innovation of customer interactions
- Innovation of resource allocation
- Interdisciplinary collaboration
- Interdisciplinary teams
- Interface standardization
- Internal collaboration
- Internal communication
- Internal coordination
- Internal integration
- Internal optimization
- Internal skill development
- Interoperability
- IT-skills
- Lack of employees
- Lack of experience
- Management of physical & human resources
- Monetary value of data
- Multi-actor environment
- New ways of customer interaction
- Novel revenue streams
- Operating risks
- Outcome based contracting
- Outsourcing
- Partner involvement
- Performance contracting
- Pricing of new services
- Recombination
- Resource reconfiguration
- Resource sharing
- Service-centered customer interaction
- Service culture
- Service efficiency
- Standardization
- Strategy alignment
- Supplier collaboration
- Surveillance
- Top-level support
- Top management support
- T-shaped data scientists
- T-shaped employees
- Upstream collaboration
- User-centric perspective

Appendix 3: First and second order codes

(1) External collaboration	(2) Internal collaboration	(3) Human IT resources	(4) Customer-oriented culture and Strategy	(5) Data-oriented culture and strategy
· Co-creation in value networks	· CEO involvement	· Employee training	· Business model reconfiguration	· Agile processes
· Co-creation	· Cooperative productivity improvement	· IT-skills	· Customer integration	· Centralized vs. decentralized data analytics
· Co-innovation	· Creation of analytics departments	· Lack of employees	· Customer needs	· Combination of products and services
· Cooperative value innovation	· Cultural change	· T-shaped data scientists	· Customer requirements	· Data culture
· Data provision by customers	· Data silo integration	· T-shaped employees	· Customer satisfaction	· Data-driven mindset
· Downstream collaboration	· Decentralized structures	· Management of physical & human resources	· Customer-centric value innovation	· Data-oriented culture
· Ecosystem setup	· Interdisciplinary collaboration	· Lack of experience	· Customer-oriented attitude	· Digitalization capabilities

(1) External collaboration	(2) Internal collaboration	(3) Human IT resources	(4) Customer-oriented culture and Strategy	(5) Data-oriented culture and strategy
· External collaboration	· Interdisciplinary teams		· Service-centered customer interaction	· Explicit strategy
· Innovation of cooperation	· Internal collaboration		· Service culture	
· Innovation of customer interactions	· Internal communication		· Service efficiency	
· Multi-actor environment	· Internal coordination		· User-centric perspective	
· New ways of customer interaction	· Internal integration			
· Operating risks	· Internal optimization			
· Outsourcing	· Internal skill development			
· Partner involvement	· Top-level support			
· Resource sharing	· Top management support			
· Supplier collaboration	· Strategy alignment			
· Upstream collaboration				
· Control of skills				

(6) Data access, collection, and ownership	(7) Revenue models	(8) Resource recombination	(9) Standardization	(10) Data privacy
· Automated data exchange	· Data monetization	· Innovation of resource allocation	· Interface standardization	· Data privacy & security
· Big data expertise	· Design of new revenue models	· Recombination	· Interoperability	· Data security
· Continuous data exchange	· Novel revenue streams	· Resource reconfiguration	· Standardization	· Surveillance
· Control of knowledge	· Outcome based contracting			
· Data access	· Performance contracting			
· Data exchange	· Pricing of new services			
· Analytical capabilities	· Monetary value of data			

(6) Data access, collection, and ownership	(7) Revenue models	(8) Resource recombination	(9) Standardization	(10) Data privacy
· Data interpretation capabilities · Data ownership · Data possession · Digital platform · Data processing capabilities				

Appendix 4: Literature review concept matrix

	External collaboration	Customer-oriented culture and strategy	Data access, collection and ownership	Human IT resources	Internal collaboration	Data-oriented culture and strategy	Revenue models	Resource recombination	Standardization	Data privacy
Aho (2015)		X		X	X	X	X			
Anke (2018)	X		X			X	X			
Ardolino et al. (2017)		X	X							
Belvedere et al. (2013)	X		X		X					
Beverungen et al. (2017)	X		X							
Bigdeli et al. (2017)	X									
Brax and Jonsson (2009)	X	X								
Brown (2017)								X		
Bullinger et al. (2015)				X	X	X				
Cenamor et al. (2015)	X			X				X		

	External collaboration	Customer-oriented culture and strategy	Data access, collection and ownership	Human IT resources	Internal collaboration	Data-oriented culture and strategy	Revenue models	Resource recombination	Standardization	Data privacy
Chen and Zhang (2014)										X
Chen et al. (2016)	X			X						
Cohen et al. (2017)	X		X					X		X
Coreynen et al. (2016)	X	X								
Davenport (2014)	X	X		X			X			
Demirkan and Delen (2013)	X	X			X					X
Demirkan et al. (2015)	X	X	X	X			X		X	X
Exner et al. (2018)	X	X	X		X					
Fu et al. (2018)	X									
Gebauer et al. (2017)	X	X								
Geum et al. (2015)		X						X		
Goduscheit and Faullant (2018)	X	X	X			X				
Golightly et al. (2017)	X			X		X				
Grubic and Jennions (2017)	X		X	X			X		X	
Grubic and Peppard (2016)	X	X	X	X		X				
Helfat and Raubitschek (2018)	X	X		X	X		X			

	External collaboration	Customer-oriented culture and strategy	Data access, collection and ownership	Human IT resources	Internal collaboration	Data-oriented culture and strategy	Revenue models	Resource recombination	Standardization	Data privacy
Herterich et al. (2016)	X				X				X	
Herterich et al. (2015)	X									
Hou and Neely (2018)	X	X		X	X		X			
Immonen et al. (2016)	X	X								
Jonsson et al. (2008)	X	X								
Kaltenbach et al. (2018)			X						X	
Kamp et al. (2016)	X		X	X	X			X	X	X
Kampker et al. (2018)		X	X		X	X				
Klein et al. (2018)	X	X	X	X		X	X		X	
Kowalkowski et al. (2013)	X	X								
Kowalkowski and Brehmer (2008)	X	X								
Kusiak (2009)	X	X								X
Kusiak (2017)	X		X						X	X
Lim et al. (2018)	X		X							
Lenka et al. (2017)	X	X		X						

	External collaboration	Customer-oriented culture and strategy	Data access, collection and ownership	Human IT resources	Internal collaboration	Data-oriented culture and strategy	Revenue models	Resource recombination	Standardization	Data privacy
Lerch and Gotsch (2015)	X	X		X						
Nino et al. (2015)	X		X							
Opresnik and Taisch (2015)	X					X				
Persona et al. (2007)	X	X		X						
Pigni et al. (2016)	X		X	X		X				
Remane et al. (2017)								X		
Robinson et al. (2016)	X	X			X		X			
Rymaszewska et al. (2017)	X		X	X	X					
Sanders (2016)	X			X	X	X				X
Schüritz et al. (2017)	X		X	X	X	X	X			
Sorescu (2017)	X							X		
Story et al. (2017)	X	X		X		X				
Tao et al. (2018)		X	X							
Teece (2018)		X					X		X	
Thoben et al. (2017)	X						X		X	X
Troilo et al. (2017)		X		X	X	X		X		

	External collaboration	Customer-oriented culture and strategy	Data access, collection and ownership	Human IT resources	Internal collaboration	Data-oriented culture and strategy	Revenue models	Resource recombination	Standardization	Data privacy
Urbinati et al. (2018)	X	X	X	X	X		X	X		
Vendrell-Herrero et al. (2017)	X							X		
Wen and Zhou (2014)	X				X				X	
Westergren (2011)	X			X						X
Yoo et al. (2012)	X		X		X			X		
Wiesner et al. (2016)	X									
Zeng and Glaister (2018)	X		X	X	X	X			X	
Zheng et al. (2017)		X			X			X	X	
Zheng et al. (2018)	X		X							
Zolnowski et al. (2017)							X			
Zolnowski et al. (2016)	X	X	X							
SUM	54	32	26	25	20	15	14	12	12	10

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Declarations

Conflict of interest The authors have no competing interests to declare that are relevant to the content of this article.

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