

Design Principles for Industrial Data-Driven Services

Can Azkan , Frederik Möller , Lennart Iggena, and Boris Otto 

Abstract—The continuously growing availability and volume of data pressure companies to leverage them economically. Subsequently, companies must find strategies to incorporate data sensibly for internal optimization and find new business opportunities in data-driven business models. In this article, we focus on using data and data analytics in product-oriented industrial companies. Although data-driven services are becoming increasingly important, little is known about their systematic design and development in research. Surprisingly, many companies face significant challenges and fail to create these services successfully. Against this background, this article presents findings from a multicase based on qualitative interviews and workshops with experts from different industrial sectors. We propose ten design principles and corresponding design features to successfully design industrial data-driven services in this context. These design principles help practitioners and researchers to understand the peculiarities of creating data-driven services more in-depth on a conceptual, technical, and organizational level.

Index Terms—Data-driven services, design principles, design science, digital business models, service innovation.

I. INTRODUCTION

THE importance of data as a resource for business model innovation and the resulting data-driven products and services have experienced a significant rise in attention [1], [2]. Companies can develop and offer data-driven products through systematic data collection, management, and analysis. In particular, some of the most valuable companies globally, such as Amazon, Apple, Facebook, or Google, show how to make innovative use of data and leverage the advantages of information and communication technologies [3], [4]. A tangible example from the manufacturing industries is the service *predictive maintenance* that predicts asset and tool failure to help customers prevent machine downtimes, reduce maintenance costs, and increase efficiency [5]. German manufacturers, such as SIEMENS and BOSCH, already offer these services successfully, resulting in long-term customer relationships [6], [7], extending existing

products and services [8], or creating competitive advantages [9]. However, developing data-driven services is still a significant challenge for most traditional companies. They struggle to leverage data-driven service innovation and exploit the full potential of data [10]–[13]. Especially, product-centric companies face significant challenges in developing data-driven services [14]–[16]. That is a stark contrast to young tech companies, such as those mentioned above, as they orient their business models toward novel technologies and develop new ones themselves.

The advent of digital-native start-ups in many industries comes alongside disruptive innovation based on data (e.g., see Möller *et al.* [17] in the logistics industry). Contrarily, traditional companies have decades of experience in their specific domain. They possess critical industry knowledge but still lack essential skills in leveraging data analytics, software engineering, or new data-related technologies, such as Internet-of-things (IoT) [18], [19]. Only about one in two companies generate moderate revenues through digital initiatives, while a quarter even loses money [20].

This article addresses precisely that issue. Because of the above, this article aims to generate prescriptive design knowledge in the shape of design principles to assist practitioners and researchers in designing industrial data-driven services [21]. We see formulating design principles as sensible, as codifying prescriptive design knowledge for reuse can ease the burden of developing new solutions, reduce the number of iterations they require, and ultimately save costs and increase efficiency [22], [23]. Subsequently, our *research question* reads as follows: *How to design successful industrial data-driven services?*

Next to the literature corpus, our primary data reside in a multicase study of six real-world digitization projects cases to elicit theory as prescriptive design knowledge [24], [25]. Design principles are a part of the *theory for design and action* [26] and are meta-artifacts that explicitly support the successful creation of artifacts [27]. Our goal is to develop constructive knowledge [28] that contributes to theory and practice [29]. Design principles are a suitable medium for that purpose as they are an accepted linguistic vehicle to communicate recommendations for action to practitioners and managers [30]. The design principles are then translated into an action guide that links them together and creates a meaningful order to facilitate their application [31].

This article is organized as follows. After the introduction, the theoretical background of this research is presented by defining data-driven services, analyzing existing design principles and explaining service-dominant logic (SDL) as a theoretical lens. That is followed by our research design, consisting of data

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collection and analysis and the process of design principle development in Section III. Section IV contains our findings from the identified metarequirements (MR) to the derived design principles, including corresponding design features. Section V evaluates the results with experts from industry and research. Finally, we offer both practical and scientific contributions in Section VI, considering limitations and future research.

II. THEORETICAL BACKGROUND

A. Industrial Data-Driven Services

The machine and equipment manufacturing market is characterized by intense and aggressive competition [15]. Shortening of product life cycles, interchangeability of products, price erosion and pressure on margins, internationalization, and, especially, digitization are increasingly causing structural changes in markets and companies [32]. Subsequently, these technological innovations and changing customer demands confront companies with the need to adapt how they do business rapidly [33]. In particular, expanding the product range with services can be a means of differentiation and provide a robust market defense in an industry characterized by a cost-intensive product base [34].

Unlike products, services often deliver a reoccurring income stream, require less capital investment, and generally lead to higher margins [35]. The transition from manufacturing and selling products to providing services and solutions is called *servitization* [36]. For example, besides offering vehicles, truck manufacturers sell maintenance, service packages, and driver-training programs [35].

The transformational developments in information and communication technologies enable new service innovation based on collecting, processing, and using data [37]. In many organizations, data availability leads to searching for new ways to gain a competitive advantage or better serve customers or clients [38]. Thus, on the one hand, companies use and analyze data to support internal decision-making and to improve the usage of existing assets [39]. On the other hand, data exploitation is seen as a new source for innovating service offerings [40], [41]. With empowering technologies, such as sensor technology, IoT, and cloud computing, product-centric companies can analyze data from and about their customers, creating new, more timely, and accurate services, which are more appealing than purely nondigital services [38], [42]. Data and analytics support the customer's decision-making process giving sound data-based insights and creating new customer value [39], [43]. These novel value propositions use data as the key resource and are called *data-driven services* [10], [13].

Azkan *et al.* [5] conceptualized the nature of data-driven services by building a taxonomy that established an in-depth understanding of their structure. The taxonomy uses the theory of service-oriented business models as a structuring frame to characterize data-driven services along the metadimensions of *value proposition*, *value creation*, *value delivery*, and *value capture* (see Fig. 1). This enables a holistic view of the topic to analyze data-driven services thoroughly, considering multiple facets of their development.

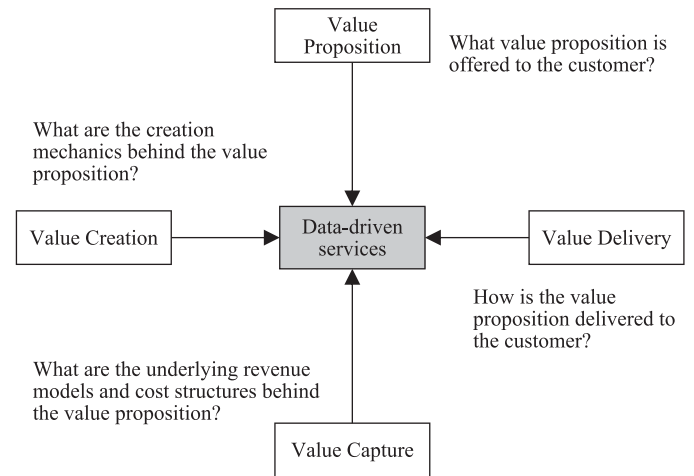


Fig. 1. Impact of business model dimensions on services.

Since data-driven services rely on data, the taxonomy distinguishes various data types (e.g., process and product data) and data sources used to create customer values [44]. Complex algorithms form the services' core function and are distinguished into descriptive, diagnostic, predictive, and prescriptive analytics types [38], [45]. Focusing on manufacturing industries, the primary value of a data-driven service can be machine and equipment condition monitoring, decision support for operational and strategic business decisions, quality control of products on the production line, or predictive operations, e.g., daily customer orders or future orders supplier pricing. Therefore, data-driven services spawn efficiency gains of underlying processes, improved quality of manufactured products, new data-driven insights for decision-making, or whole new offerings enabled by data analytics and artificial intelligence [5]. This holistic view allows for deeper investigations so that the taxonomy structure provides the framework to derive appropriate design principles systematically [46].

Related concepts to data-driven services include product-service systems (PSS) or service-oriented architecture (SOA) and require demarcation. In the case of PSS, the marketable combinations of *tangible products* and *intangible services* are specifically investigated to meet the customer's needs [47], [48]. The product/service ratio can vary, either regarding the fulfillment of the function or the economic value [49]. A distinction is essentially made here between product-oriented, usage-oriented, and results-oriented services [47]. Thus, PSS cover a broader spectrum than data-driven services. However, some parallels, especially in the case of results-oriented services, are shown in the results section of the design principles.

In contrast to PSS, the focus of SOA is on examining the software architecture of distributed systems at the technical level [50]. In essence, SOA can be understood as a paradigm that describes how existing IT components such as databases, servers, and websites can be encapsulated into services and coordinated to combine their performance into higher level services [51]. Thus, in contrast to the objective of this study, the focus of SOA

is on an overly technical level, which is why the basic principles can only be applied here to a limited extent.

B. Existing Design Principles for Service Development

Building on the findings described above, a systematic literature review was conducted according to Webster and Watson [68] and vom Brocke *et al.* [69] to foster reuse and analyze the current availability of design principles for developing data-driven services [70]. We used the databases *Scopus*, *ScienceDirect*, and *AIS eLibrary* to collect papers that report on design principles in the domain of data-driven services [71]. In the search for existing design principles, terms closely related to *data* are deliberately used. The search strings contained all combinations of *design principles*, *design rules*, or *guiding principles* on the one hand and the other hand *data-driven services*, *digital services*, *data-based services*, *smart services*, or *data services*. The search produced 109 publications, which we screened for duplicates and relevancy. Table I lists the final sample of nine papers reporting on design principles.

We defined a total of five criteria to filter the papers based on the overall goal of this work, the development of data-driven services from the perspective of practitioners, and the derivation of design principles in the context of design science research (DSR).

- 1) *Data as a key resource*: The core aspect of this article is the development of design principles for data-driven services. Thus, considering the digital component or data as a core resource is essential in evaluating existing design principles. In particular, information and communication technologies and the handling and processing of data must form the basis for providing services [5], [79].
- 2) *Design principles as meta-artifacts*: Another essential aspect is the underlying methodology when developing design principles. Therefore, design principles are particularly relevant for the work, which explicitly refer to the artifact development and reflect prescriptive knowledge in the form of recommendations for action [60], [80].
- 3) *Empirical investigation*: To achieve scientific rigor and practical relevance by DSR [71], attention is also paid to the empirical reference of the publications presented. For this purpose, interviews or case studies may have been conducted for artifact development, for example, so that the derived knowledge addresses existing challenges from practice.
- 4) *Business model perspective*: A relevant aspect for evaluating data-driven services is the holistic view from the business model perspective. That includes essential business model elements, such as the value proposition, value creation, value delivery, and the underlying revenue model [5].
- 5) *Industrial services*: The fifth and final criterion is based on industrial services. That refers in particular to services from the B2B sector. Here, design principles are examined that focus on product-related machine-related services, which are provided as technical objects of commercial customers [81].

TABLE I
RELEVANT STUDIES PROPOSING DESIGN PRINCIPLES IN THE FIELD OF
DATA-DRIVEN SERVICES

No.	Title	Sources
1	The digital service innovation canvas	[72]
2	Six Principles for Successful Data-driven Service Innovation	[10]
3	Recombinant Service Systems Engineering	[73]
4	Design Principles for Analytics-based Services	[74]
5	Towards a Smart Services Enabling Information Architecture for Installed Base Management in Manufacturing	[75]
6	Design Principles for Route Optimization Business Models	[76]
7	Making Data Tangible for Data-driven Innovations in a Business Model Context	[77]
8	Stepwise Evolution of Capabilities for Harnessing Digital Data Streams in Data-Driven Industrial Services	[12]
9	Theory-Based Design Principles for Digital Service Innovation	[78]

First, Rose *et al.* [72] aim to develop a business model canvas adaption for digital services in the context of e-government using action design research (ADR). They initially derived theory-based design principles evaluated through workshops with representatives from the public sector to support the development process. Therefore, this article does not provide insights for the industrial sector and does not highlight data as the key resource in service design. The work of Kampker *et al.* [10] focuses on formulating principles for industrial data-driven services without using a DSR approach. Beverungen *et al.* [73] derived design principles from the literature to design a method for service systems engineering but do not conduct empirical research. Another canvas was developed by Hunke and Kiefer [74] that instantiates the created design principles within a DSR project. The methodological tool assists practitioners in designing analytics-based services, but there is no domain focus set. The same applies to Kühne *et al.* [77], who developed design principles for data-driven business models assigned to the business model canvas elements. More technical work is provided by Dreyer *et al.* [75], where design principles of information architecture for smart services are developed following the ADR approach. Thus, the principles do not address the design of services directly. Möller *et al.* [76] investigated data-driven business models in the logistics sector. As a result, they provide design principles for the successful design of route optimization business models derived from user reviews. Guiding principles with recommendations of actions for developing industrial data-driven services are elaborated by Herterich *et al.* [12]. Nevertheless, the work does not follow a DSR approach or take a business model perspective. The last identified paper by Rose *et al.* [78] provides design principles for digital service innovation. Again, data do not play a pivotal role in service design, and the principles are derived theoretically.

To summarize our findings, existing research insufficiently addresses the guided development of data-driven services through design principles. While nearly all the works examined

have a digital component in the design principles, the methodology by which the artifact development has been undertaken varies widely. For example, Rose *et al.* [72], Möller *et al.* [76], and Hunke and Kiefer [74] used DSR first to gather MR and then formulate design principles. At the same time, other authors do not develop design principles using this methodology. About empirical investigation, it appears that some authors utilize case study research and expert interviews for data collection (cf., [12], [74]). In contrast, others rely on purely literature-based data collection (cf., [73]). A key aspect in developing data-driven services is the holistic consideration of business model dimensions, not omitting any relevant aspects in the design. Here, it is particularly apparent that some publications often only consider partial aspects of a business model (cf., [74]), or do not take a business model perspective at all (cf., [10], [12], [72]). Furthermore, the focus on industrial data-driven services is only found in the works of Kampker *et al.* [10] and Herterich *et al.* [12]. Considering everything, there is no research found that conceptualizes design principles for industrial data-driven services from a business model perspective following a DSR approach or that can be transferred to its own research field. Therefore, the presented work tackles the identified research gap.

C. Service-Dominant Logic

We use SDL as a theoretical lens to analyze the development of data-driven services. In SDL, the customer does not simply consume a service or good but participates in the value creation process [52], [53]. In contrast to a goods-dominant perspective, services are considered the foundation for an economic exchange instead of goods [54]. SDL focuses on “value-in-use” rather than “value-in-exchange” [5], [55]. That implies that value is not determined by the features of an offering but by the value perceived by the user [43], [52]. A critical factor in SDL is value cocreation that describes collaborative and reciprocal value creation between actors and entities through mutually beneficial integration of resources [43], [56]. In the context of data-driven services, customers are mainly involved in value creation since data are the central resource, primarily coming from sensors and IoT devices generated in customer processes [5], [53], [57]. Blaschke *et al.* [56] differentiated the knowledge of SDL into four levels to reflect these levels’ descriptive and prescriptive nature.

First, SDL is grounded in and derived from four *metatheoretical foundations (level I)* [58]. Actor-to-actor networks describe the network-centric perspective of SDL, where all actors are resource integrators. Second, resource liquefaction refers to the digital decoupling of information from its associated physical form or device to make information more useful and shareable. Third, resource density implies efficiently mobilizing contextually relevant knowledge (resource). Fourth, resource integration emphasizes that all innovation results from combining existing resources as any resource can never be used in isolation. From a theoretical perspective, the next level proposes a set of 11 *foundational premises (level II)* [52], [55], [59]. Here, SDL reconceptualizes *service* (the process of doing something beneficial for and in conjunction with another), *resources* (anything an

actor can draw on for support), *exchange* (the exchange of the performance of specialized activities instead of the exchange of outputs), and *value* (occurs when the offering is useful to service beneficiary) [56], [58]. From the foundational premises, on a managerial level, nine *derivative propositions (level III)* are derived as practical implications [56], [59]. The overarching theme of these derived proposals is innovation and competition through service thinking [56]. That underscores the need to shift from a purely product-oriented mindset in traditional industrial companies to a network and service-oriented perspective. Innovation occurs in collaborations through cocreating and coproducing activities that lead to competitive advantages. In the study of Blaschke *et al.* [56], they extended this view of SDL by adding another level that includes *design knowledge (level IV)* to guide the design of digital value cocreation networks informed by service thinking. We follow this approach to derive design principles and MR to develop data-driven services successfully.

III. RESEARCH DESIGN

A. Method for Design Principle Development

The structure of our research design follows the recommendations of Möller *et al.* [60], which is one of the few methods explicitly aimed at developing design principles (see Fig. 2).

- 1) First, one must define the solution objective (SO), which explains what artifact the design principles address is supposed to achieve. In our case, the SO reads as follows: “*Assist practitioners and researchers in designing industrial data-driven services successfully*” (see Section I).
- 2) Second, the method requires outlining the research context. The study at hand is a *multicase study* that applies various submethods in each case to analyze qualitative data within a *DSR project*. For example, these include interviews with experts, case analysis, and desk research (see Section III-A).
- 3) Third, one should decide on an essential epistemological pathway distinguishing between *reflective* (usually ADR) [61], that develops prescriptive design knowledge on something that has been done [62] or *supportive*, i.e., generating prescriptive design knowledge before artifact design. In our case, we use the *supportive* approach, as we collect data before designing new data-driven services.
- 4) Fourth, when developing design principles, one must identify a suitable knowledge base. For this purpose, on the one hand, the scientific literature was examined in general to better understand the phenomenon of data-driven services (see Section II-A), e.g., through reviewing existing design principles in the context of industrial data-driven services (see Section II-B). This knowledge, in turn, formed the basis for conducting multiple case study research in which *six companies* were accompanied in how they have developed data-driven services (see Section III-B). For the empirical data collection, 19 workshops were initially held for this

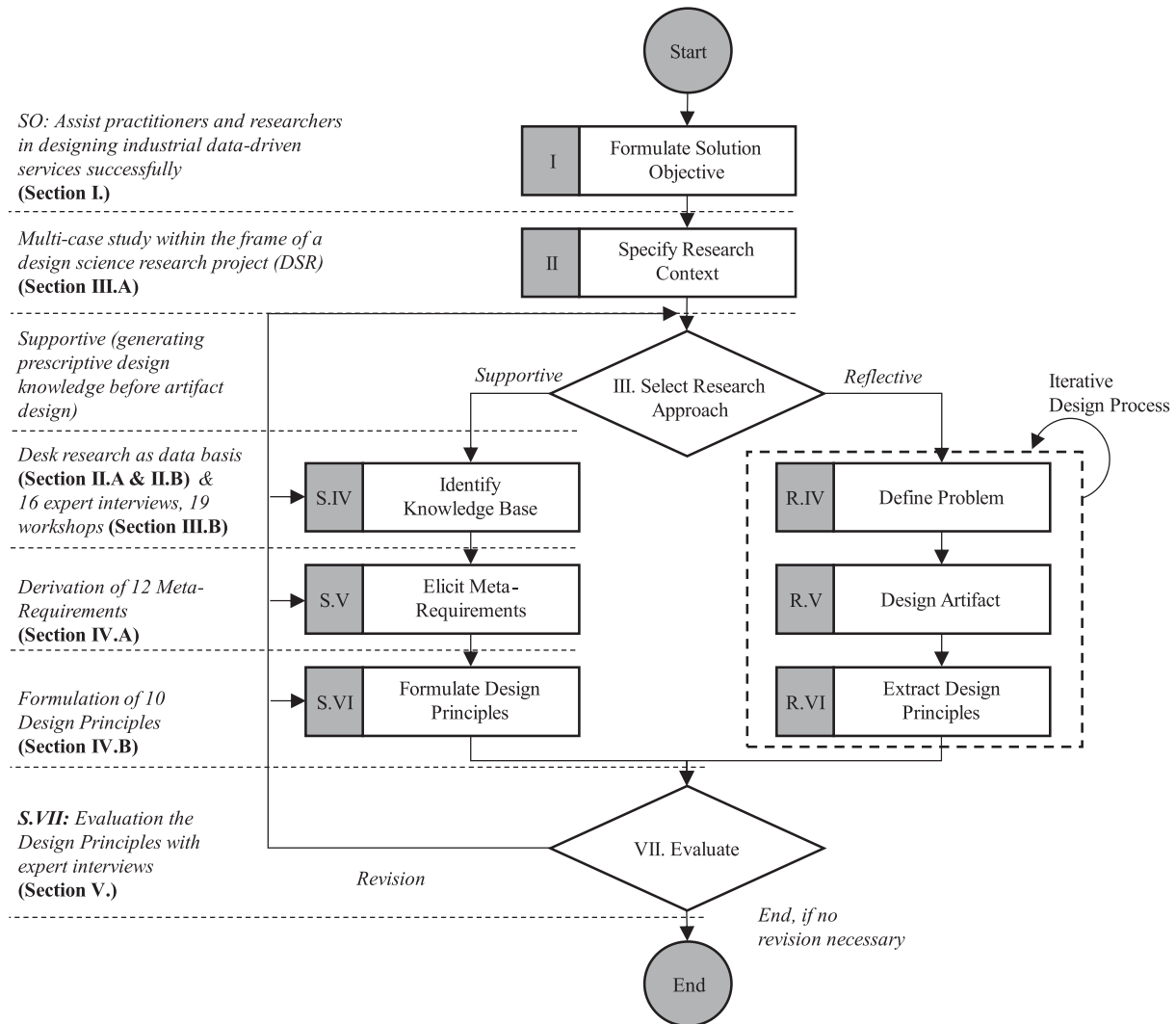


Fig. 2. Method for developing design principles based on Möller *et al.* [55].

purpose and complemented by expert interviews with 16 experts to collect data engrained in practitioners' unique experience, knowledge, and environment.

- 5) We complement our research through data triangulation with desk research to gather more information about existing use cases. For this purpose, company reports or presentations were analyzed to understand the context of the development of data-driven services (see Section IV-A). Fifth, one must elicit MR from the data, i.e., requirements that address the class of artifact "industrial data-driven service" [63]. For that, we use data analysis methods of grounded theory (GT) and logical content aggregation.
- 6) Sixth, we aggregate MR logically and formulate design principles that address them (see Section IV-B) [64]. Significantly, each design principle must address at least one MR to fulfill *value grounding* [65]. When formulating design principles, one can draw from multiple formulation templates. Even though there is a variety of formulation

TABLE II
CONSTRUCTS OF DESIGN PRINCIPLES ACCORDING TO [21]

Construct	Description
Prescriptive Statement	"Provide the system with [material property - in terms of form and function] in order for users to [activity of user/group of users - in terms of action], given that [boundary conditions - user group's characteristics or implementation settings]."
Action	"(...) actions made possible through the use of an artifact."
Material Properties	"(...) material properties making that action possible."
Boundary Condition	"(...) boundary conditions under which the design principle will work"

templates (for an overview, see Cronholm and Göbel [66]), the study follows the recommendation of Chandra *et al.* [21] as it includes and demarcates constructs that the design principles must be composed of. Table II gives

definitions of each construct and the linguistic template for formulating the prescriptive statement.

- 7) Finally, we evaluate the design principles in a round of expert interviews (see Section V), following the evaluation criterion of Iivari *et al.* [67].

B. Case Study Research for Data Collection

Case study research is widely used in IS research and is suitable for unraveling complex relationships in a real-world context [82]. That is especially the case when the causes of organizational challenges need to be investigated, where the boundaries between real phenomena and their environment cannot be identified [82]. In this specific context, we report on a multiple case study. Compared to single case studies, multicase studies produce more robust and generalizable findings [83]. The cases (see Table III) represent real-world digitization projects in data-driven service design. They are the cumulative result of two consortium research projects. We collected data on the cases between April 2018 and March 2021. The cases span various industries, i.e., manufacturing, engineering, logistics, and telecommunication. However, the unifying element and the object under study is the common feature of designing data-driven services, i.e., its shared phenomenon [84]. While cases A, D, and E aim to expand the core business with digital offerings as a traditional company, cases C and F explore entirely new business opportunities based on data. In case B, the company reacts to customer demands and implements a *track and trace* solution.

In addition to the six case studies presented in this article, further expert interviews were conducted with other companies. Some of the experts who were interviewed came from the immediate environment of the companies with which the case study was conducted and are, for example, the users of the data-driven service and IT service providers. They provide the analysis processes or cloud platforms. A detailed description of the position and the interview duration can be found in the Appendix (see Tables VI and VII). Thus, a total of 16 interviews were conducted as part of this work on data collection. The tables also contain further information on the respective case study.

Three different research methods were used to investigate and analyze the case studies, including (*focus group*) *workshops*, *expert interviews*, and *secondary research*, i.e., *desk research*. The goal behind conducting workshops is to elicit views and opinions on specific topics through a moderated survey of groups or individuals documented [85]–[87]. Focus group workshops are especially suitable for knowledge generation in DSR [88], [89], which forms the basis to further develop the acquired knowledge with other research methods [90]. Therefore, each case study’s initial findings were supplemented, extended, and triangulated through qualitative interviews with experts [91]. Qualitative expert interviews can be defined as a systematic and theory-driven data collection procedure in the form of interviewing individuals (“experts”) who have exclusive contextual knowledge about the specific object of study [92]. Experts,

TABLE III
CASE STUDY OVERVIEW

Case Study	Industry & Business Segment	Data-Driven Services	Data Collection
A	Cement Plant Construction, Research & Development	<ul style="list-style-type: none"> Condition Monitoring Predictive Maintenance Analytics Platform 	<ul style="list-style-type: none"> 5 Workshops 3 Interviews Desk Research
B	Steel Production, Logistics	<ul style="list-style-type: none"> Track & Trace Automated Calculation of ETA 	<ul style="list-style-type: none"> 5 Workshops 1 Interview Desk Research
C	Telecommunications, Vehicle Technology	<ul style="list-style-type: none"> Data Trading of Environmental & Mobile Data 	<ul style="list-style-type: none"> 5 Workshops 2 Interviews Desk Research
D	Plant Engineering, Heat Treatment	<ul style="list-style-type: none"> Condition Monitoring Analytics Platform 	<ul style="list-style-type: none"> 4 Workshops 1 Interview Desk Research
E	Machine Tool Manufacturing, Cold Forming	<ul style="list-style-type: none"> Quality Control 	<ul style="list-style-type: none"> 1 Interview Desk Research
F	Household and Commercial Equipment Manufacturing, Digital Services	<ul style="list-style-type: none"> Pay per Use-Model 	<ul style="list-style-type: none"> 1 Interview Desk Research

thus, serve as a source for acquiring practice-oriented expertise about the contexts to be explored [93]. All expert interviews were transcribed completely in order to capture the greatest possible amount of information for subsequent analysis. The transcription and analysis of the data were performed using MaxQDA software. The experts’ interviews were structured in such a way that questions were systematically asked for each business model dimension (value proposition, value creation, value capture, and value delivery; see Fig. 1) about the challenges but also the opportunities in the development of data-driven services. This, in turn, formed the basis for deriving the various MR.

While the workshops and the experts’ interviews involved direct questioning and both research methods counted as primary research, desk research was carried out to complement them. For this purpose, additional information sources, such as websites of the relevant companies, and internal project documentation, such as presentations or videos, were used and interpolated with the primary research results [94].

To analyze both the data from workshops and experts’ interviews, we followed the GT paradigm. The goal of GT is to generate theory from empirical data and qualitative data (all kinds of data, e.g., documents, interview transcripts, or protocols) [95]. Two key concepts shape GT [96]. First, through *constant comparison*, there is no border between data collection, data analysis, and theoretical sampling (i.e., to specify which data are appropriate for the research question) [97]. As GT is a paradigm with multiple methods [98], we chose the procedural model of Izverican *et al.* [97]. The data analysis continues as



Fig. 3. Design principles for the development of industrial data-driven services.

long as theoretical saturation, i.e., the point at which no new information can be found from the data has not been reached [99]. We followed the *template coding* approach [100], [101], which prescribes predefined templates to categorize the data. Following the taxonomy of Azkan *et al.* [5], we use the dimensions shown in Fig. 1.

IV. DESIGN PRINCIPLES FOR INDUSTRIAL DATA-DRIVEN SERVICES

Based on the workshops, interviews, and desk research findings, fundamental problems and opportunities have been identified in developing and providing data-driven services. They were assigned to the taxonomy's metadimensions of Azkan *et al.* [5] and categorized to structure the problems and opportunities. Subsequently, MR could be drawn systematically, which comprise the categories into high-level classes.

A. Metarequirements

Our study elicits and defines 12 MR derived from the identified problems and opportunities, which are the basis for design principle formulation. Following Offermann *et al.* [102], we formulate the MR using "should" to indicate that they are requirements that should be fulfilled (see Table IV). Also, the requirements describe the influence or relevance of the SDL. In addition, sample quotes are provided from the case studies and interviews that formed the basis for the MR.

B. Design Principles

In total, we propose ten design principles to help companies develop data-driven services more successfully (see Fig. 3). Complementarily, we operationalize the design principle into design features (*DF*) that decouple them from their high degree of generalizability to near-instantiation level. The results were then translated into an action guide to support applying the

principles in the form of a reference book with interrelationships and a logical sequence (see Appendix, Figs. 4 and 5). A summary of the design principles and associated design features can also be found in Table V.

Design Principle 1: Life cycle of products, plants, and processes: Provide the development of data-driven services with an orientation toward customer activities among the life cycles of products, plants, and processes in order for users to generate value propositions systematically, given that customer needs in each phase of the cycles are considered.

Explanation: When developing data-driven services, companies often face the challenge of deciding which services should be developed and what order should be developed at all [103]. A detailed overview of a machine or system's lifecycle gives the service developer a better orientation as the customer's activities can be investigated [104]. Furthermore, data-driven services should be an integrated part of future product developments to foster data-driven innovation [13].

Implications: Depending on the underlying object, some phases of each life cycle can be underscored as they hold a high potential for data-driven services. *The life cycle of a product (DF1.1)* includes, for example, the quality assurance phase, wherein case E, a continuous data-driven inspection of the manufacturing process for specified product dimensions or surface quality, was offered to customers, enabling automatic detection of product defects. During the production phase of a *life cycle of a plant (DF1.2)*, various systems, machines, and tools interact to achieve the desired results. Therefore, supervision of individual components plays an important role, so a condition monitoring service based on sensor data, as in case A, provides an efficient and convenient real-time solution. In the *lifecycle of a process (DF1.3)*, the implementation phase can be optimized by data-driven services, such as in case B, where a GPS-based calculation of the estimated arrival time of incoming trucks is made so that downstream steps can be aligned with it.

TABLE IV
METAREQUIREMENTS

#	Data-driven services should...	Example Quote	<i>„Where customers are afraid of, that's a little bit like car insurance tracking you as you drive, that customers are afraid that certain misconduct will be documented and that misconduct will then fall on their feet for certain warranties.“</i> Interviewee case A 1 – Manufacturing Inc.
MR1	...clearly demonstrate the added value of data-driven services in both technical and economic terms. The case studies reveal a significant hurdle in showing the added value of a data-driven service. Frequently, expected added values were mentioned to potential customers, such as process optimization, cost, and time savings. These could not be sufficiently substantiated using key figures. So-called "soft" factors were also mentioned, such as strengthening customer loyalty which, however, could not be quantified. Therefore, it is necessary to identify the added value for the respective target group already during the development of data-driven services through concrete key figures. Regarding SDL, determining the added value of a service is a challenging task.	MR5	...be developed and offered in collaboration with strategic partners to compensate for own weaknesses and enable mutual learning. The case studies demonstrated that diverse expertise is needed for developing data-driven services. The required expertise includes specific processes, necessary skills in handling big data, data analytics, and IoT platforms' development and operation. Especially, product-oriented companies lack these new skills, making collaboration with innovative startups, IT service providers, or other industry partners that have already developed and established similar services becomes an important aspect. This creates a strategic network of cooperating companies that jointly engage in value-creating activities through exchanging data, services, and financial resources. In particular, this encourages the value creation described in networks, in which companies contribute their operands and operand resources beneficially.
Example Quote	<i>„That's a very, very big problem for us, because we have many long-established colleagues, especially in production, who stick to their structures and for whom even simple systems initially cause excessive demands and rejection. These are discussions such as: "I already have enough to do, why do I have to use the next tool again?"“</i> Interviewee L – Service User	Example Quote	<i>„There I would distinguish between the soft things: Marketing, website, sales concept, etc. I think we had a preparation time of six months before we had our first customer. Technologically, what's behind it, we have a partner. We didn't do it all ourselves. This is a platform, there's definitely four years of work behind it.“</i> Interviewee case F 1 – Billing Service Provider Inc.
MR2	...bundle different data sets and data sources to obtain and predict more in-depth information about the underlying processes. Data-driven services mainly use customer data like machine, process, or product data. We only found a few relevant data sets during the study's offset, such as vibration data or oscillations of a machine engine. These were used for condition monitoring. However, the systematic addition of additional data sets and the bundling of additional information revealed new service opportunities. Subsequently, these required new data, such as weather data or environmental data on ambient temperatures. The SDL perspective supports the enrichment of data-driven services with additional resources, consisting of data since the object of consideration is value creation networks. Integrating further resources can supplement the value proposition towards the customers with more in-depth information.	MR6	...be established in a customer-centric and data-driven organizational culture that promotes service innovation based on new technologies. New data-based value offerings differ significantly from traditional services and physical product sales, requiring a major shift to a new strategic direction and an agile organizational culture. The studies have shown that it proves to be laborious to establish the willingness to develop such offerings throughout the whole company. Thus, product-focused companies need change management to create an open mindset and a corporate culture embracing data-driven services and encouraging innovation. Since this significantly influences the competitiveness of a company, it can also be argued that not only the internal corporate culture at the service provider is of great relevance, but also the culture of the service user to establish the data-driven service.
Example Quote	<i>„That was such a side effect of seeing, based on the GPS data of the individual push barge, what the fill level of the port actually is. When it's foggy, you just don't know it. That came to our attention more or less by accident that we could use the track and trace system for that as well.“</i> Interviewee case B 1 – Steel Producer Inc.	Example Quote	<i>„But then it also fails largely because the refinery is really an old process and a lot of people who are there are often not open to something new. It's not like it's a new technology, it's not like we're building a new plant where the thinking is completely new. No, it's always said by the masters and operators that we've been doing it this way for 30 years and that's the way it's going to stay. And that, of course, perpetuates itself, even when new employees start.“</i> Interviewee G – Service User
MR3	...ensure that the quality of the data is sufficiently high and sensors work properly in manufacturing conditions. Data quality is essential to make valuable conclusions for data-driven services. The case study primarily uses data sets that predominantly originate from sensors of machinery that usually operate under harsh requirements (e.g., with a lot of dust, vibration, or noise). SDL does not mention data and information quality explicitly. Nevertheless, a valid assumption seems that resources needed to add value to services require sufficiently high quality in order to create value for the end-user.	MR7	...be designed with customers under consideration of their specific needs and their existing IT infrastructure. A further issue is that many companies are not yet digitally mature enough to easily send and receive data, which poses additional challenges for data-driven service creation. In case A, the customers operate their cement production plants worldwide, for example, in Siberia. The challenge here is that due to extreme weather conditions such as snowstorms, it is sometimes impossible to establish an Internet connection to send data. Because of this, data-driven solutions need to be implemented that also work locally so as not to be influenced by such external environmental factors. This is also in line with SDL, which sees value creation in networks as necessary and therefore has to consider the customer's IT infrastructure.
Example Quote	<i>„Data quality is of course very, very important. There's the saying "shit in, shit out" and that's de facto also the case. If I want to rely on something and work in a data-driven manner, then the data is of course the basis. And if something doesn't fit, then that's bad. Then I might draw the wrong conclusions at the end that don't correspond to reality.“</i> Interviewee H – Service Provider	Example Quote	<i>„What we also found in the first attempts to do projects is, the digital maturity, both at the capability level to send data and at the level to receive and consume sent data, is not there. That what's inhibiting projects today is not the reasonableness of the basic idea, but the trivial level of IT capability that companies actually have.“</i> Interviewee I – Service Provider
MR4	...guarantee secure and trustworthy data exchange. The data often contains sensitive information about customers' production processes or personal data, e.g., about machine operators. In cross-company data exchange, there is often a significant concern among service users that this data could leak to competitors and cause damage to the company. Also, users worry about the loss of warranty claims if a data-driven service provides information about using a system. Similar to the previous meta-requirements, creating trust is not a direct component of SDL. However, it can also be assumed that each building block is considered necessary to achieve the objectives (including competitive advantages and value proposition).		

TABLE IV
(CONTINUED)

MR8	...offer appropriate revenue models based on the specific requirements of both the customer and the provider.	Example Quote	<i>„So that we optimize the plant for the customer, increase production, reduce energy. All this in the form of AI solutions that we run on site or in the cloud, which can then control the plant more optimally. [...] We are talking about neural networks, anomaly detection and everything that is possible with AI. Currently, we are more or less using the preliminary stage. A program that looks on site at certain data that we record, such as vibration and production. If the vibration goes up, it automatically adjusts the feed down.“</i> Interviewee case A 2 – Manufacturing Inc.
	Another aspect is the change in revenue models when offering data-driven services, for example, by moving from a classic service purchase to a license or usage rate model. A condition monitoring service, e.g., runs all the time, so one-time payments do not affect the long-term interaction between the service provider and user. Therefore, in the case studies, the companies elaborate with their customers' different revenue models in which both the service users and providers can extract added value. This underlines the aspect of SDL that goods can be seen as a kind of distribution mechanism for services, where value unfolds through the individual use of the customer.		
Example Quote	<i>„Then, for example, with the controller, we follow two different approaches. On the one hand, also the license model that we install the controller and as long as the customer uses it, the customer pays us sum X per month. Because we assume that he will make Y additional profit in this month. That's why we want to get a certain amount of that. The other approach for the controller would be this performance-based solution. That we only get paid for what we have really given the customer as added value.“</i> Interviewee case A 2 – Manufacturing Inc.		
MR9	...be designed around existing objects and processes and likewise integrated into future product developments.	Example Quote	<i>„Lastly, the creation of data-driven services calls for agile development techniques. All companies behind the case studies emphasize the relevance of considering customer needs at an early stage of development. It has been shown that an efficient way to obtain customer feedback and to implement useful functions is to prototype minimum viable services (MVS). To this end, in case E, for example, pilot customers are specifically involved with whom the core functionalities of service are tested together, thus enabling savings in money and time while at the same time providing the data-driven service as early as possible.“</i> Interviewee H – Service Provider
	A data-driven service always refers to a real-world object such as machines, systems, or vehicles. The case studies involved services for machine tools for forming round steels, crushing machines for crushing limestone, industrial washing machines, or annealing systems for heating materials. Data-driven services should also be considered in prospective product developments, e.g., by installing sensors, even if the specific use case is not yet defined. As the consideration of the eighth meta-requirement from the SDL perspective has already shown, the meta-requirement described here also reinforces the fact that goods can be seen as the basis for transmitting added value in the form of services.		
Example Quote	<i>„Without a real world and without technical products, data is worth nothing. That's why our model is to link the real world and technical products with data and thus offer all participants in the entire value chain real added value in the form of data-driven services.“</i> Interviewee M – Service Provider		
MR10	...incorporate suitable algorithms for data processing and analysis to gain insights, optimize processes, or enable autonomy.	Example Quote	<i>„Yes, and of course it also requires the customer where you can test on it, you can't develop things like that in the lab because you don't have experience data. You can't make a million parts in our lab. That's an incredible amount of money and we didn't have the capacity. That means you have to go into the field, you have to have an MVP, Minimal Valuable Product, in other words a device that just about works, that can do something.“</i> Interviewee case E 1 – Machine Tool Builder Inc.
	A key finding from the case study research is that data-driven services have varying levels of maturity, which ultimately have varying business value for both the service provider and service user and can be attributed to different levels of analytics. For example, in case D, there are descriptive methods used to report the condition of the heat treatment process, while in the case study, diagnostic procedures uncover cause-effect relationships. The aspect of increasing the business value of a data-driven service depending on the complexity of the knowledge used is underpinned by the SDL. On the one hand, this can increase the added value for the customer with increasing specialization. On the other hand, this creates competitive advantages for the service provider, including through differentiation from competitors and the increased (monetary) benefit for the customer.		
MR11	...offer digital interfaces that meet customer preferences and requirements.		
	An important part is a digital interface and how a service user interacts with the data-driven service. All six case studies have established or aim to develop a digital platform as the core interaction element where data and information can be shared and the service can be used. Nevertheless, many customers are skeptical about cloud platforms, so the topic of edge computing is emerging. The advantage lies in the combination of cloud and local technologies. The algorithms and applications run locally at the customer's site but can be managed by the provider via a central management system. Offering user interaction interfaces can increase the benefit for customers (see SDL).		
Example Quote			
MR12	...be co-developed with a pilot customer in an agile process using MVS that meets the customer's minimum requirements.		
	Lastly, the creation of data-driven services calls for agile development techniques. All companies behind the case studies emphasize the relevance of considering customer needs at an early stage of development. It has been shown that an efficient way to obtain customer feedback and to implement useful functions is to prototype minimum viable services (MVS). To this end, in case E, for example, pilot customers are specifically involved with whom the core functionalities of service are tested together, thus enabling savings in money and time while at the same time providing the data-driven service as early as possible. This observation is complemented by SDL, as it describes the value creation of services as a reciprocal process between the service provider and service user.		
Example Quote			

Design Principle 2—Data quality and availability: Provide the data-driven services with data from multiple sources, such as sensors, that meet data quality standards in order for users to be able to draw meaningful conclusions from the analyses, given that data quality management is implemented and sensors work properly.

Explanation: An essential factor in data-driven services is the data themselves. On the one hand, it is necessary to have enough data to develop algorithms that can, for example, estimate when a machine component in a system needs to be replaced (predictive maintenance). On the other hand, the data must also meet various quality criteria necessary to create and use the services so that

data quality management becomes an important management task [105].

Implications: For a sufficient provision of the amount of data in certain data quality, the data-driven service to be provided (e.g., condition monitoring or predictive maintenance), as well as corresponding *data quality criteria (DF2.1)*, must be defined in advance. In the specific context of the industrial environment, the data often come from sensors that collect the data [5]. It must be ensured that the sensors capture the data correctly and have a sufficiently high resolution. Therefore, relevant criteria are correctness, accuracy, actuality, consistency, and reliability. In case C, the company collects mobile data that are highly time-critical, so the timeliness of the datasets has a major impact on their value. To achieve the right quality level, specific *measures to increase and maintain data quality (DF2.2)* need to be implemented, such as the appropriate component design in the construction of a plant to ensure that process-related influences on the sensors can be excluded or reduced, e.g., to reduce dust accumulation as in the cement production of case A. The collected data from the respective sensors and machines can further be processed on different systems. Using suitable communication protocols (*DF2.3*) to enable data exchange is necessary. Examples of communication protocols or machine interfaces are S7 RFC1006, Modbus TCP, MQTT, REST-API, or EtherNet/IP. For this purpose, the so-called edge devices were developed in all case studies, making it possible to read out machine data via various communication protocols.

Design Principle 3—Performing data analytics: Provide the data-driven services with data analytics in order for users to draw insights from the collected data that lead to business decisions, given that appropriate methods of analysis are used depending on the goal to be achieved.

Explanation: Data itself are useless if there is no exploitation process and the insights gained are not used for data-driven decisions [106]. There are different types of analytics for different objectives, whether visualization of data in tables and charts or advanced methods for predicting certain results.

Implications: *Descriptive analytics (DF3.1)* describes models in which insights into past events are provided. They view data statistically and provide information in reports, data visualizations, or dashboards. In case D, the company wants to digitize the heat treatment process and offer digital evaluations to customers. *Diagnostic analytics (DF3.2)* take descriptive analytics a step further, aiming to derive causalities as to why something occurred. That takes place in case E, where the data-driven service identifies defects in the product line. Based on historical data, machine learning models are used in *predictive analytics (DF3.3)* to predict what will most likely happen in the future. The company in case A wants to implement a predictive maintenance service, where the failure of a particular component is predicted before it occurs so that it can be acted upon proactively. In contrast, *prescriptive analytics (DF3.4)* suggests various courses of action and answers what should be done based on existing data and its resulting predictions. However, although various

analytics have been used across the case studies examined, no data-driven service has yet been developed that uses prescriptive analytics.

Design Principle 4—Return on Investment (ROI): Provide the data-driven services with adequate information on potential returns on investment through key performance indicators in order for users to convince customers, given that sufficient metrics can be collected to determine the ROI.

Explanation: This principle illustrates the need to map the added value of data-driven services based on ROI to convince decision-makers to use the services offered. It is necessary to provide measurable metrics and derive technical and economic KPIs within the constraints. That is also in line with the results of other scientific studies, which show that it is necessary to highlight the added value [13], [103], [107].

Implications: ROI is usually the most important indicator for measuring a company's success [108]. If this is applied to data-driven services' success, it is possible to assess whether the savings and benefits outweigh the costs. The key performance indicators should directly answer customer needs, which can be collected in advance through *interalia* surveys and workshops [10]. A common representation for visualizing ROI is the Du-Pont key figure system, where the ROI is composed of profit margin and assets turnover, which in turn are derived from further key figures. Thus, in terms of data-driven services, there are important *key figures to revenue (DF4.1)*, such as the selling price of the underlying product for which a service enhances quality or production volume, which is what happens in case E with the quality control service. Regarding *key figures for operating costs (DF4.2)*, a data-driven service, such as in case B, provides route optimization and transparency that significantly impacts a company's logistics costs. Other aspects include *invested capital (DF4.3)*, where a data-driven service minimizes the overall wear and tear of a plant through, for example, predictive maintenance, as in case A, so that critical components and parts are replaced at the optimal time.

Design Principle 5—Revenue model: Provide the data-driven services with suitable revenue models in order for users to obtain a secure and long-term cash flow, given that customer requirements are met and the added value can be shown.

Explanation: The application of digital technologies and the use of data as a core resource for creating services enable different revenue models accompanied by increased customer benefits. The revenue model must be designed to allow an individual customer to take advantage of the services [79]. At the same time, there is a transfer of risk to the service provider since, in the case of solution-oriented models, revenue is only generated if the data-driven services are offered to fulfill their performance promise. That also shows close parallels to results-oriented PSS, in which the result for the customer is given a high priority. Design features for revenue models have also been developed accordingly.

Implications: One possibility of generating revenue for data-driven services is introducing a *subscription model (DF5.1)*. The service user pays a monthly fee, observed in case A.

Furthermore, the fees for subscription models can be staggered concerning the scope of functions or quantity. In a *pay-per-use* (DF5.2) revenue model, the service user pays to depend on the service frequency. In this type, usage can be attributed to the number of times the service is called up, the amount of data volume used or analyzed, or the use of a machine's capability. In case F, the company provides its washing machines to business customers but remains the owner. It then generates money using the machines, resulting in a long-term cash flow over its lifetime. If the service goes beyond and, for example, provides clear recommendations for action or intervenes automatically in the plant processes, *performance-based contracting* (DF5.3) can be used. Here, the service provider receives a percentage share of the service's additional profit, so the customer only pays if the service succeeds. Offering a novel, nontraditional revenue model based on digital technologies can be recognized as a competitive advantage [109]. The case studies have shown that the companies and the customers are interested in such a model, but implementation presents some hurdles, as systems are complex. The accurate baseline of value added by the service is difficult to quantify.

Design Principle 6—Data processing and service provision: Provide the data-driven services with digital interfaces such as web interfaces, API, or mobile applications in order for users to facilitate the usage so that customers are willing to take advantage of them, given that customers' demands and technical requirements are considered.

Explanation: The delivery of the services should be on time and with the promised quality [106]. Digital interfaces can build easy access for the generated value and should consider customer demands and technical requirements.

Implications: A *cloud platform* (DF6.1) can be a convenient way for service delivery as the service user can access analysis results and recommendations for action via a web interface. The use of an IoT platform as a cloud service brings advantages for service providers in that the platform is very flexible in architecture and scalability [110]. A platform can also be accessed on different end devices, such as computers, tablets, or smartphones. All companies are already using or are developing platforms to provide their services to customers about the case studies. In contrast to the use of cloud computing, *edge computing* (DF6.2) has emerged, in which the use of data-driven applications and the data processing behind it takes place within a network [111]. Keeping data on the local network increases security by reducing the number of system boundaries crossed. That plays a significant role, especially for sensitive datasets, and enhances trust for the use of data-driven services. Edge computing is also characterized by short latency times and high speeds as the computing operations directly in the system [112]. Particularly, this is relevant for time-critical applications [113]. That could also be observed, e.g., in case A, where some customers are located in exotic places that require local solutions as no stable internet connection can be guaranteed around the clock.

Design Principle 7—Data security and sovereignty: Provide the data-driven services with data security and sovereignty among all data-related activities through secure processes, legal frameworks, and usage policies in order for users to foster customers' trust in data sharing, given that IT-infrastructures and regulations are considered.

Explanation: Cross-company data exchange is crucial for developing and using data-driven services. Data security and protection build a significant aspect in the creation as industrial companies, particularly, fear the loss of data and sensitive information of production processes and operating secrets. Secured data exchange and the preservation of data sovereignty lead to trust and transparency between the service provider and user and contribute to the conviction of data sharing [114]. Data sovereignty means that the data provider controls the data after being sent [115]. It has been shown that companies are more willing to send data if they know what happens to it, and they can still decide who can view it [116].

Implications: When developing data-driven services, it is necessary to address data security early and use current security standards for data exchange. Secure processes can be implemented through *technological measures* (DF7.1), such as firewalls, encryption, or authentication. In case A, the company implemented two-factor authentication on its platform to ensure that customers could only access the data they are supposed to and not gain insights from competitors. The other layer addresses *organizational measures* (DF7.2) to achieve data security. Here, contractual agreements are highly recommended, as in case B. The company has committed to not storing any personal data from the trucks and not taking any negative consequences.

Design Principle 8—Organizational culture and mindset: Provide the development of data-driven services with an agile and customer-centric environment within the company in order for users to promote a service mindset and an understanding of the benefits of data-driven applications, given that employees have the opportunity and willingness to participate in service development and idea generation activities.

Explanation: Leaps in innovation in information technology, the complexity of products or intercultural cooperation, and the associated new data-driven services affect change management topics. Cultural change management should change the mentality from product-centric mindsets to service orientation, which is crucial for long-term success and continuous service innovation. In this context, it is essential to involve all employees early, set goals, and provide a company vision [10]. In terms of the customers, a data-driven mindset is also needed to use such services [103].

Implications: Change management provides four dimensions in which an organization should implement appropriate measures [117]. Within the corporate *strategy* (DF8.1), the service provider's framework conditions are defined for the pursued vision for offering data-driven services. To this end, the operational, functional areas (e.g., R&D, sales), and business units

TABLE V
MR, DESIGN PRINCIPLES, AND DESIGN FEATURES (WITH RELATIONS IN BRACKETS)

Meta-Requirements	Design Principles			Design Features
MR1: demonstrate added value in both technical and economic terms (DP1, DP2, DP3, DP4, DP5, DP6, DP8, DP9, DP10)	DP1: Life cycle of products, plants & processes (MR1, MR7, MR9, MR11)	Action Material Properties Boundary Conditions	generate value propositions systematically orientation towards customer activities among the life cycles of products, plants, and processes customer needs in each phase	DF1.1: Life cycle of a product DF1.2: Life cycle of a plant DF1.3: Life cycle of a process
MR2: bundle different data sets and data sources (DP2, DP3, DP4)	DP2: Data quality and availability (MR1, MR2, MR3, MR7, MR9, MR11)	Action Material Properties Boundary Conditions	draw conclusions from the analyses data from multiple sources, like sensors, in sufficient amounts that meet data quality standards data quality management, sensors	DF2.1: Data quality criteria DF2.2: Measures to increase and maintain data quality DF2.3: Communication protocols
MR3: ensure that the quality of the data is sufficiently high and sensors work properly in manufacturing conditions (DP2, DP3)	DP3: Performing data analytics (MR1, MR2, MR3, MR10)	Action Material Properties Boundary Conditions	draw insights from the collected data that lead to business decisions data analytics methods of analysis, goals to be achieved	DF3.1: Descriptive analytics DF3.2: Diagnostic analytics DF3.3: Predictive analytics DF3.4: Prescriptive analytics
MR4: guarantee secure and trustworthy data exchange (DP7)	DP4: Return on Investment (MR1, MR2)	Action Material Properties Boundary Conditions	convince customers adequate information on potential returns on investment through key performance indicators sufficient metrics	DF4.1: Key figures for revenue DF4.2: Key figures for operating costs DF4.3: Invested Capital
MR5: guarantee secure and trustworthy data exchange (DP8, DP9, DP10)	DP5: Revenue Model (MR1, MR8, MR9)	Action Material Properties Boundary Conditions	obtain a secure and long-term cash flow suitable revenue models customer requirements, added value	DF5.1: Subscription Model DF5.2: Pay per Use DF5.3: Performance-based contracting
MR6: establish a customer-centric and data-driven organizational culture (DP8)	DP6: Data processing and service provision (MR1, MR7, MR9, MR11)	Action Material Properties Boundary Conditions	facilitate the usage digital interfaces customers' demands, technical requirements	DF6.1: Cloud-platform DF6.2: Edge Computing
MR7: design with customers under consideration of their specific needs and their existing IT infrastructure (DP1, DP2, DP6, DP7, DP10)	DP7: Data security & sovereignty (MR4, MR7, MR11)	Action Material Properties Boundary Conditions	foster customers' trust in data sharing data security and sovereignty among all data-related activities IT-infrastructures, regulations	DF7.1: Technological measures DF7.2: Organisational measures
MR8: appropriate revenue models (DP5)	DP8: Organizational culture & mindset (MR1, MR5, MR6, MR12)	Action Material Properties Boundary Conditions	promote a service mindset and an understanding of the benefits of data-driven applications agile and customer-centric environment employees	DF8.1: Strategy DF8.2: Culture DF8.3: Technology DF8.4: Organization
MR9: design around existing objects and processes and likewise integrated into future product developments (DP1, DP2, DP5, DP6, DP9, DP10)	DP9: Expert knowledge & skills (MR1, MR5, MR9, MR11)	Action Material Properties Boundary Conditions	achieve the most profound results expert knowledge and complementary competencies data analytics capabilities, process knowledge	DF9.1: Relevant expertise DF9.2: Building of expertise and strategic partnerships
MR10: advanced algorithms for data processing and analysis (DP3)	DP10: Minimum Viable Services (MVS) (MR1, MR5, MR7, MR9, MR12)	Action Material Properties Boundary Conditions	reduce risks and costs minimum viable services customers needs, technical requirements	DF10.1: Functional service prototype DF10.2: Pilot customers
MR11: digital interfaces (DP1, DP2, DP6, DP7, DP9)			<i>no further DP</i>	
MR12: co-develop with a pilot customer in an agile process using MVS (DP8, DP10)			<i>no further DP</i>	

(e.g., divisions, business units) are aligned with the corresponding objective. In case F, the company established a spin-off for the data-driven business because it allowed it to achieve its goals more efficiently and more time by being much more agile. *Cultural aspects* (DF8.2) affect corporate values, norms, and attitudes. A new model of mentality implies learning new values and the willingness and ability to unlearn and abandon outdated routines, leading to the adaptation of more effective behavior [16]. In this context, viewing data as an operational resource must be part of the organizational culture [106]. An essential aspect of this is actively bringing in critical employees who are reluctant to embrace new digital technologies and changes [18]. Regarding the *technology dimension* (DF8.3), technological developments and, in particular, the increasing use of ICT have a formative influence on corporate change. These can be identified in communication between people, more efficient process operations, or new business areas. Nevertheless, the use of new technologies such as artificial intelligence can lead to possible rejection on the part of the service user, as the service value creation processes are not understood. Therefore, the functionality of the algorithms and processes behind data-driven services and the associated recommendations for action must be made very clear and transparent. To address the cultural and technological aspects, targeted change management processes were initiated in cases A–C and E, in which different initiatives were launched. These initiatives aimed to align the mindset of employees with digital technologies, make processes leaner, or focus on customer orientation. For example, critical employees were also explicitly involved in developing the strategic orientation to increase the solution orientation by transferring responsibility. Finally, *organization* (DF8.4) refers to establishing organizational units, regulating process flows, and defining areas of responsibility. In case A, the concern set up a new business unit for data analytics, which different business departments can draw on.

Design Principle 9—Expert knowledge and skills: Provide the development of data-driven services with expert knowledge and complementary competencies in order for users to achieve the most profound results, given that data analytics capabilities and process knowledge are present.

Explanation: This design principle stresses the need to bring different competencies to create data-driven services together. That starts with data scientists who are experts in handling data and ends with process experts who can evaluate the analysis results. While topics such as connectivity and storage are often tackled jointly with partners and the process knowledge already exists within the company, strategic core competencies, such as data analytics, should be developed by the companies themselves [118].

Implications: To systematize and investigate *relevant expertise* (DF9.1), it is suitable to refer to the data value chain, which includes the stages of data generation and collection, preprocessing and curation, data integration and data analysis, combination with domain knowledge and experience, and the use of the gained insights for business decisions. Additionally, there is a need to know data-related legal topics, service

design, and business development. For example, in case A, the company had significant concerns about legal issues, so it had to find a deep solution before implementing newly developed data-driven services with customers. Therefore, *building expertise and strategic partnerships* (DF9.2) becomes crucial for the successful development of data-driven services, for which there are several approaches. Larger corporations that are financially strong enough can build up entire departments in data science, for example, to bring the necessary knowledge into the company, as in case A. They can develop these skills by either hiring new talents and/or training their current employees [119]. Smaller and medium-sized companies do not usually have this financial strength [103], so they procure services for building up digital structures from external companies, which was true in case B and D. Either way, it has been shown that cross-company cooperation, especially with start-ups, is worthwhile, as knowledge can ideally complement each other.

Design Principle 10—Minimum viable services (MVS): Provide the development of data-driven services with the idea of MVS in order for users to reduce risks and costs, given that technical requirements and customer needs are considered.

Explanation: This design principle addresses the development process, which is regarded as multilayered and characterized by different aspects. It is based on lean startup thinking, which coined the term minimum viable product (MVP), and revolves around the rapid development of a product that is just about ready to work [120]

Implications: A key success factor in developing data-driven services is the involvement of users of the service. The service can be developed as efficiently as possible in several iterations. The focus here is on developing a *functional service prototype* (DF10.1) that covers the minimum user requirements so that the service fulfills its intended purpose [121]. That enables testing under real market conditions and rapid feedback collection [118]. That was realized in case A as the company launched its platform with initial rudimentary services, which could be developed step by step. The development of a functional service prototype is accompanied by the need to involve *pilot customers* (DF10.2) as service users. Thus, these pilot customers play a key role in the service development, which is why the choice is crucial for future success as they represent the entry market and should be able to give critical feedback. In case E, the company developed its data-driven service hand in hand with pilot customers to gain market understanding, receive meaningful feedback, and clarify the concrete added value for potential customers. Table V provides the relationships between the MR, design principles, and design features.

C. Action Guideline

By translating the results above into an action guideline, we pursue the goal of helping the core target group of this work, the business model developers and service designers. Subsequently, they should apply the design principles and thus support and

facilitate the service development process in the form of a set of rules in a given sequence [31], [122]. For this purpose, the prescriptive knowledge acquired is related to each other and subdivided in the form of a total of eight actionable steps, as can be seen in Figs. 4 and 5 within the Appendix.

- 1) First, a classification is made of the perspective from which the data-driven services are developed. A distinction is made between a manufacturing company and a “pure” IT service provider. The relevance is that a manufacturing company develops data-driven services around its existing products and can, thus, exert a significant influence on, for example, data availability and necessary communication interfaces. On the other hand, an IT service provider develops data-driven services for the customer’s most existing processes and systems. As a result, specific process knowledge may be required when creating the services, which a pure IT service provider usually does not possess.
- 2) The second stage covers three design principles, which address “soft” criteria in service development and generally describe which aspects should be considered in development.
 - i) *Design principle 8* addresses considering the own and customer’s corporate culture and mentality. Remarkably, that is relevant to reducing resistance in developing services based on new digital technologies. For example, suppose a manufacturing company develops new data-driven services. In that case, the company may face more significant challenges than an IT service provider. That is often in addition to the existing core business (the pure sale of machines, including maintenance contracts).
 - ii) The development of data-driven services requires distinct interdisciplinary expertise (*Design principle 9*). That includes business model development experts, process engineers, IT developers, and process experts. From the manufacturing company’s perspective, process and procedure experts are available, but IT knowledge is often lacking to develop data-driven services comprehensively. At IT service providers, relevant IT skills are available. Still, they must also develop services in collaboration with specialists who know the basic mechanics of systems or the underlying processes to extract meaningful information based on the processing and analysis of data.
 - iii) An important aspect is the lean development of services and the rapid collection of feedback from pilot customers. That is addressed in the context of *design principle 10* to build a MVS. This approach can prevent erroneous development and thus save costs and time.
- 3) The third stage shows then what should be developed. *Design principle 1* involves looking at the life cycles of products, systems, and processes. A manufacturing company can, thus, systematically screen relevant areas of its product range and develop data-driven services for individual phases of the lifecycle. Likewise, an IT service provider looks at the life cycles of the customer’s products and processes to work together for which phase a data-driven service adds value.
- 4) The two manufacturing companies and IT service provider streams are merged from the fourth stage onward since the following design principles have similar characteristics for both perspectives. *Design principle 2* considers data availability and the required data quality for the individual use case. After selecting and focusing on a specific phase of a lifecycle, attention must be paid to what data are needed and how the data can be collected.
- 5) Analyzing the collected datasets represents the core aspect in the value creation of data-driven services addressed by *design principle 3*. Subsequently, it is essential to consider the purpose of data analysis and the added value behind the service. For example, descriptive analysis methods are suitable for creating condition monitoring services, whereas predictive analysis methods are necessary for a predictive maintenance service.
- 6) Based on the type of analysis used and, thus, the classification of the added value of the service, the ROI can be determined as *design principle 4* indicates. This stage illustrates the added value of a data-driven service using concrete key figures. The aspect that data-driven services can substantially influence key figures, such as reducing unplanned downtime or increased product quality, is reflected in ROI. The influence can be divided into sales revenue, operating costs, and invested capital.
- 7) Next, the revenue model should be defined, supported by *design principle 5*. Finally, in the case of a concrete quantification of the added value based on performance indicators, performance-based contracting can be selected, demonstrating the effectiveness of the data-driven service and providing the user with transparency about the success. Otherwise, subscription models or the transition to an operator model in a pay-per-use model are also suitable for data-driven services.
- 8) The final stage of the action guideline deals with the location of data processing and the provision of services (*design principle 6*), which goes hand in hand with ensuring data security and sovereignty (*design principle 7*). Data processing and service provision can essentially be differentiated into using external networks and servers or the company’s own. Since this issue is associated with cross-company data exchange, data security and sovereignty play a significant role. These must be implemented through technological and organizational measures to make concerns about the loss of sensitive customer data disappear.

V. EVALUATION

Evaluation is a significant step in artifact construction in DSR to demonstrate its practical relevance [71]. We use the

framework of Ivari *et al.* [67], [123], who propose five criteria to assess the design principles' usefulness. The order of the criteria plays a role in evaluating design principles. If one of the criteria is not met, all following criteria are irrelevant. The first criterion concerns the *accessibility* of the design principles. That means that the target group must be able to understand and comprehend the respective design principles. The *importance* of design principles relates to their relevance in practice and the primary target group. The third criterion describes that the developed design principles must show *novelty* for the target group and confirm what is already known from everyday life. Usability describes the realistic applicability of the design principles, which is manageable or feasible under a practitioner's control. For this purpose, the design principles should focus on the essential goal and the related system addressed by the created artifact. *Actability* means that a design principle is manageable and feasible in practice, i.e., it is under the control of the respective practitioners and can be realistically implemented. The fifth criterion relates to the *effectiveness* or usefulness of design principles for an individual or an organization. According to [67], this involves looking particularly at how valuable the design principles are for the user and to what extent they can be recontextualized in their current form. However, the challenge here is that this effectiveness needs to be assessed consistently. The application of design principles would need to be done by real people, in a real organization, over a more extended period. Nonetheless, with the help of practitioners, the potential of a design principle can be evaluated.

Four industry experts and two scientists from the same research area evaluated the results. Integrating additional research experts is valuable in covering a different perspective concerning methodological derivation and formulation [118]. We first sent a questionnaire with the respective design principles and the evaluation criteria to the individual experts in preparation for the evaluation interview to evaluate our findings. Subsequently, the design principles, including the associated design features and the developed action guideline, were critically discussed based on the criteria.

- 1) *Accessibility*: All experts from research and industry confirmed the first criterion of accessibility concerning comprehensibility and traceability. In particular, the detailing of the design principles in the form of design features and ultimately the transfer into a guideline for action was seen as very helpful so that the accessibility of the entire design principles was increased via the presentation of the big picture (see Appendix, Figs. 4 and 5).
- 2) *Importance*: Building on the first criterion, the importance of the formulated design principles was rated as very high, particularly by the industry experts. The principles address highly relevant problems in the everyday lives of practitioners in the development of data-driven services, where topics such as data security, cloud computing, the presentation of added value, or cultural aspects were especially emphasized. However, the importance of the design principles varies depending on which company was

interviewed and the role of the interviewed expert. For example, it was brought out that the calculation of ROI is not necessary to present the added value of a service if a customer requests a data-driven service and the need is therefore customer-driven.

- 3) *Novelty*: The assessment of the novelty of a design principle depends heavily on the expertise and role of the expert surveyed. While, for example, the third design feature of data analytics and the associated description of different analysis methods do not represent novelty for IT experts and data scientists, the systematic consideration of the product life cycle or the ROI, on the other hand, represent new aspects for this group of experts.
- 4) *Actability*: First of all, the general formulation of the design principles offers sufficient flexibility to be applied to different domains in the industry while at the same time providing adequate formulation precision and, thus, concretization of the application content. In a further step, the design features with a higher level of detail represent a first instantiation step that increases the applicability of the design principles from a practical point of view. For example, it was noted by several experts that the measures for improving the data quality of the sensor-based data or the table for building up expert knowledge could be seen as a kind of catalog of measures or reference work that provides support for the development of data-driven services. Finally, the related design principles and associated design features in the form of an action guide were seen as a great help, which strongly supports the applicability of these and shows the interrelationships of different design principles by placing them in order.
- 5) *Evaluation of effectiveness*: As an overriding conclusion on the effectiveness criterion, the usefulness of the design principles in their entirety for application in practice was emphasized by all the experts. For example, it was explicitly noted that the systematization of different life cycles, such as products or plants, is a great help in identifying relevant services and, thus, prioritizing development processes. The effectiveness of the design principles is also increased because the areas of value proposition, value creation, value delivery, and value capture are addressed in a targeted manner. Thus, all relevant dimensions of a business model are taken into account. Furthermore, by including customer requirements in service development and considering relevant areas of change management, pertinent assistance influences the change in a company's ability to innovate or the quality of its services.

VI. CONTRIBUTIONS, LIMITATIONS, AND OUTLOOK

A. Scientific Contributions

This article contributes codified prescriptive design knowledge elevated from experts' experiences and the environment

into generalized meta-artifacts. As the field of data-driven business is getting ever-more relevant, so is the importance of research on it. Our design principles contribute to prescriptive knowledge for data-driven service design in manufacturing industries and the scientific knowledge base. Other research can draw from them, extend them through additional research approaches, or refine them based on their respective areas of interest. They expand the knowledge base specifically for manufacturing research, yet they also have implications on a general scope. For example, design principles, such as the prescription of adequate data quality and data availability, are not exclusive to manufacturing industries but apply to most industries. In our case, the data quality depends on industrial sensors' sensory integrity and accuracy (e.g., they might be prone to collect incorrect data if they are dusty). Furthermore, it was also possible to show the extent to which the theoretical lens on SDL could be reflected in the results of the case study research and explain real-world phenomena.

B. Managerial Contributions

This article develops ten design principles from six case studies. Each design principle represents a qualitatively assessed area of importance in data-driven services design in manufacturing industries. As per the "practical ethos" of design principle formulation, we explicitly developed the design principles to be reusable in other instances. That ensures that practitioners from different domains can use the design principles in their respective application scenarios. Thus, this work results help practitioners understand the fundamental challenges and opportunities to develop data-driven services. The design principles can help address challenges from the ground up and enable a more prosperous and systematic service development based on data-driven innovation. That begins with selecting relevant services over the product life cycle of a product or process and extends to the need for cultural change management to obtain a data-driven mindset. The design principles' structure via action, material properties, and boundary conditions allow clear implications and recommendations for action, even if they are still flexible enough to enable generalization.

C. Limitations

Formulating design principles is a commonly accepted way to codify prescriptive design knowledge. Yet, design principles come with some natural limitations. First and foremost, the design principle instantiation is not a guarantee for success as it must be embedded into the user's personal experiences and professional environment. Even if an evaluation has been carried out with industry experts, the effectiveness, for example, can only be checked in a limited form in advance. The design principles can and should be seen as meta-artifacts that help designers achieve designs more efficiently, but not as a definitive and stand-alone promise of success.

Additionally, the design principles originate from qualitative research, i.e., workshops and interviews within case study research. They only reflect the synthesized findings based on that study and our qualitative interpretation of essential issues in the experts' statements and observations. The fact that the experts stem from the product-oriented industry means that the design principles cannot be directly transferred to other branches. That could result in different problems and opportunities in other areas, leading to various design principles and, thus, recommendations for action.

D. Outlook

The idea of data-driven services is becoming increasingly popular in the industrial context. To this end, companies seek to cooperate and exchange data with existing and new customers to lay the foundation for such new services. The derived design principles offer a profound way to assist in designing and developing data-driven services. However, further research should, on the one hand, tie up to our results with more data sources (e.g., more interviews, case studies) to obtain a more comprehensive view of industrial data-driven services. Furthermore, the application in other sectors might be considered, leading to new findings and potentially enhancing our results. Our focus is on the B2B industry. Considering services in the B2C segment (e.g., tourism sector, smart city, or fitness applications) could provide further insights since much different data are generated in the private consumer sector, ultimately benefiting from the service. For example, while companies today still need to be strongly incentivized to share data with other companies, private consumers are more willing to send their data to companies to use their services or platforms. That would also mean that the design principles developed would need to be modified. For example, calculating the ROI or corporate culture is probably not highly relevant for the private consumer. Also, since the generation of data in the B2C segment often takes place via end devices such as smartphones, the data quality, in this case, is not as critical as, for example, the generation of data in cement production as this can have more significant sources of error.

Furthermore, the design principles and the action guideline should be transformed into a method that successfully provides a structured approach for developing new data-driven services.

It has been shown that by bundling different datasets, new insights can be gained that make it possible to increase the added value of a service. In this way, data become a product, and service providers could selectively purchase different datasets to improve a service's effectiveness further. Consequently, further research could be conducted into which datasets from which domain and what quality must be available so that data-producing companies can trade in data themselves or service developers can specifically purchase data to generate deeper insights from data analyses.

APPENDIX

See Tables VI–VII and Figs. 4–5.

TABLE VI
OVERVIEW OF WORKSHOPS AS WELL AS INTERVIEWS CONDUCTED AS PART OF CASE STUDY RESEARCH AND SHORT DESCRIPTION OF THE CASES

Case Study	Participants	Contents	Duration
Case A (Manufacturing Inc.)	<ul style="list-style-type: none"> 6 representatives from industry (business development managers, project managers, technical managers, portfolio managers, senior engineers (2x)) 8 representatives from research institutes (postdocs, scientific assistants) 	<ul style="list-style-type: none"> Definition of the case study Problem definition Case formulation Collection of requirements 	5:00 hours
	<ul style="list-style-type: none"> 4 representatives from industry (product managers for digital services, technical managers, innovation managers) 6 representatives from research institutes (postdocs, scientific assistants) 	<ul style="list-style-type: none"> Intelligent services Creation of services Revenue streams Customer pain points 	6:30 hours
	<ul style="list-style-type: none"> 5 representatives from industry (digital service product manager, technical manager & quotation & order management (2x)) 6 representatives from research institutes (postdocs, scientific assistants) 	<ul style="list-style-type: none"> Analysis of business processes Value co-creation with different actors Definition of roles 	5:30 hours
	<ul style="list-style-type: none"> 3 representatives from industry (project manager, technical manager, senior engineer) 	<ul style="list-style-type: none"> Legal topics Governance structure 	4:30 hours
	<ul style="list-style-type: none"> 6 representatives from research institutes (postdocs, scientific assistants) 	<ul style="list-style-type: none"> Design of the platform architecture 	
	<ul style="list-style-type: none"> 4 representatives from industry (project manager (2x), technical manager, portfolio manager) 6 representatives from research institutes (postdocs, scientific assistants) 	<ul style="list-style-type: none"> Presentation and discussion of the project results 	3:00 hours
	<ul style="list-style-type: none"> Project Manager (No. 1#) 	<ul style="list-style-type: none"> Expert Interview 	0:28 hours
	<ul style="list-style-type: none"> Service Manager (No. 2#) 	<ul style="list-style-type: none"> Expert Interview 	0:44 hours
	<ul style="list-style-type: none"> Development Engineer (No. 3#) 	<ul style="list-style-type: none"> Expert Interview 	0:41 hours
Short Description of Case A	<p>For several decades, Manufacturing Inc. has been manufacturing machines and plants which customers use for the production of cement plants. In this use case, so-called <i>crusher machines</i> are to be specifically digitized, and supplementary data-driven services such as predictive maintenance are to be offered. Data such as the inclined position of the roller mills [mm], power consumed by the drives [kW], and corresponding throughput [t/h] are specifically collected and analyzed for this purpose. This enables users of this data-driven service to increase the safety of a plant's operation or machine efficiency. For example, suppose the power consumed by the drives as well as the measured torques [Nm] increase sharply. In that case, this could indicate a malfunction in the plant operation that needs to be investigated.</p>		
Case B (Steel Producer Inc.)	<ul style="list-style-type: none"> 4 representatives from industry (project managers, innovation managers, portfolio development managers, senior engineers) 8 representatives from research institutes (postdocs, scientific assistants) 	<ul style="list-style-type: none"> Definition of the case study Problem definition Case formulation Collection of requirements 	05:30 hours
	<ul style="list-style-type: none"> 3 representatives from industry (product managers for digital services, innovation managers) 7 representatives from research institutes (postdocs, scientific assistants) 	<ul style="list-style-type: none"> Intelligent services Creation of services Revenue streams Customer pain points 	05:00 hours
	<ul style="list-style-type: none"> 3 representatives from industry (product managers for digital services, technical managers) 5 representatives from research institutes (postdocs, scientific assistants) 	<ul style="list-style-type: none"> Analysis of business processes Value co-creation with different actors Definition of roles 	06:30 hours
	<ul style="list-style-type: none"> 3 Representatives from industry (project manager, technical manager, senior engineer) 5 representatives from research institutes (postdocs, scientific assistants) 	<ul style="list-style-type: none"> Legal topics Governance structure Design of the platform architecture 	04:00 hours
	<ul style="list-style-type: none"> 2 Representatives from industry (project managers, service managers) 6 representatives from research institutes (postdocs, scientific assistants) 	<ul style="list-style-type: none"> Presentation and discussion of the project results 	3:00 hours
	<ul style="list-style-type: none"> Project Manager (No. 4#) 	<ul style="list-style-type: none"> Expert Interview 	0:52 hours

TABLE VI
(CONTINUED)

Short Description of Case B	Steel Producer Inc. produces almost 10 million tons of steel per year at the site where the project was carried out. Over 60 tons of iron ore are delivered each day to produce this quantity. Deliveries are made partly by rail or ship, but mainly by truck. As a result, the plant receives around 1,200 truck arrivals and departures a day, delivering the required raw materials, the manufactured products to customers, or spare parts and special machines, which can weigh up to a hundred tons. The carriers' trucks are equipped with additional devices to track their location and send the collected data to the developed platform to streamline this process. However, since some carriers already own similar devices, an API was also developed to integrate the data from different software into their own system. The data transfer is done in two ways: the truck drivers can send their location data in real-time in the stream, or this is event-driven, for example, if a traffic jam should occur unplanned.		
Case C (Telcos Inc.)	<ul style="list-style-type: none"> • 3 representatives from industry (business development manager, project manager, sales manager, data protection officer) • 3 representatives from research institutes (scientific assistants) 	<ul style="list-style-type: none"> • Definition of the case study • Problem definition • Case formulation • Collection of requirements 	5:00 hours
	<ul style="list-style-type: none"> • 2 representatives from industry (sales managers, project managers) • 6 representatives from research institutes (postdocs, scientific assistants) 	<ul style="list-style-type: none"> • Intelligent services • Creation of services • Revenue streams • Customer pain points 	4:30 hours
	<ul style="list-style-type: none"> • 3 representatives from industry (sales managers, project managers, data protection officers) • 4 representatives from research institutes (postdocs, scientific assistants) 	<ul style="list-style-type: none"> • Analysis of business processes • Value co-creation with different actors • Definition of roles 	5:30 hours
	<ul style="list-style-type: none"> • 1 representative from industry (project manager,) • 6 representatives from research institutes (postdocs, scientific assistants) 	<ul style="list-style-type: none"> • Legal topics • Governance structure 	4:30 hours
		<ul style="list-style-type: none"> • Design of the platform architecture 	
	<ul style="list-style-type: none"> • 2 representatives from industry (project managers, sales managers) • 6 representatives from research institutes (postdocs, scientific assistants) 	<ul style="list-style-type: none"> • Presentation and discussion of the project results 	3:00 hours
	<ul style="list-style-type: none"> • Project Manager (No. 5#) 	<ul style="list-style-type: none"> • Expert Interview 	0:27 hours
	<ul style="list-style-type: none"> • Sales Manager (No. 6#) 	<ul style="list-style-type: none"> • Expert Interview 	0:35 hours
Short Description of Case C	Telcos Inc. has built up expertise in the telecommunications industry over decades and is active in the project business here. A key aspect of this project business is to use its own fleet of cars to drive along various roads within Germany and measure the performance [Mbits/s] of different mobile networks. The aim of Telcos Inc. is to expand its own core business and develop new data-driven services based on existing competencies such as data collection, information processing, and the development of electronic components. The vision is to use the company's own fleet of cars to collect other data sets in addition to measuring mobile phone data. Data on the current CO ₂ content of the atmosphere [in ppm], the noise level [dB], or the solar radiation or temperature [K] on the respective road are examples of these. Various approaches to developing data-driven services were pursued during the project. One example is the sale of mobile phones, CO ₂ , and volume data to real estate platforms. This idea is that real estate objects, coupled with this information, can influence their price accordingly.		
Case D (Heat Service Company Inc.)	<ul style="list-style-type: none"> • 2 representatives from industry (business partners, project managers) • 5 representatives of research institutes (postdoc, scientific assistants) 	<ul style="list-style-type: none"> • Definition of the case study • Problem definition • Case formulation • Collection of requirements 	3:00 hours
	<ul style="list-style-type: none"> • 2 representatives from industry (business partners, project managers) • 4 representatives of research institutes (scientific assistants) 	<ul style="list-style-type: none"> • Analysis of the existing business model 	3:30 hours
	<ul style="list-style-type: none"> • 2 representatives from industry (business partners, project managers) • 2 representatives of research institutes (scientific assistants) 	<ul style="list-style-type: none"> • Recording and documentation of business processes 	4:30 hours
	<ul style="list-style-type: none"> • 3 representatives of industry (business partners, project managers) • 4 representatives of research institutes (scientific assistants) 	<ul style="list-style-type: none"> • Specification of requirements • Development of initial solution approaches, 	4:00 hours
	<ul style="list-style-type: none"> • Project Manager (No. 7#) 	<ul style="list-style-type: none"> • Expert Interview 	0:49 hours

TABLE VI
(CONTINUED)

Short Description of Case D	Heat Service Company Inc. develops and sells so-called annealing systems, which are used, for example, for the stationary heat treatment of alloyed steels in plant construction and operation. In a heat treatment process, workpieces are heated in a controlled manner for a certain time and then cooled down again. This leads to a change in the structural properties of the material, with the aim of modifying the properties of the workpiece so that they meet the requirements of the operating process. For example, this enables the weld seams of vessels or reactors to withstand higher temperatures or pressures so that they do not give way under the effect of a load. The Heat Service Company Inc. aims to increase the efficiency of existing processes, improve transparency, and the associated safety during the annealing process. To this end, data that is already available due to the existing sensor technology (e.g., temperature sensors) will be sent via the Internet to a central cloud platform using an appropriate interface (edge device or similar). This is intended to create transparency over the entire annealing process and thus take into account, in particular, the aspect of forgery protection of the reports required by the TÜV (external inspection authority).		
Case E (Machine Tool Builder Inc.)	<ul style="list-style-type: none"> Development Engineer/ Project Manager (No. 8#) 	<ul style="list-style-type: none"> Expert Interview 	1:17 hours
Short Description of Case E	Machine Tool Builder Inc. specializes in designing and manufacturing cold-forming machines. These machines are used, for example, to produce shaft types that are used for the drive train of vehicles. For this purpose, tube parts are clamped in a machine processed through various process steps (e.g., extrusion, rolling, or removal of material by milling). In order to expand its own range of services, so-called <i>data-driven quality assurance</i> was developed. During the production of drive shafts, process data is continuously collected and analyzed in real-time. If previously defined tolerance values are exceeded, the production process is automatically adjusted, thus guaranteeing specific component quality within series production. This also means that resources can be saved for complex systems, and the required know-how in a company can be reduced. The data-driven quality assurance service can also be viewed and controlled on a cloud platform web interface.		
Case F (Billing Service Provider Inc.)	<ul style="list-style-type: none"> CEO (No. 9#) 	<ul style="list-style-type: none"> Expert Interview 	0:54 hours
Short Description of Case F	The company Billing Service Provider Inc. is a spin-off of a parent company that, among other things, develops and sells industrial goods such as washing machines for major customers. The spin-off was specifically undertaken in order to move from the pure sale of washing machines to an operator model. Here, the Billing Service Provider Inc. takes over all the necessary steps to enable the operation of a washing machine, thus transferring risk from the washing machine operator to the billing service provider. In return, the car wash operator automatically pays a portion of its revenue to the billing service provider. The washing machines that are in operation are connected to the service provider's cloud system via the Internet. This enables real-time monitoring of a washing machine's condition. Furthermore, via the use of predictive algorithms, predictive procedures can be applied to optimize maintenance cycles and thus minimize costs for the billing service provider.		

TABLE VII
DETAILS OF THE SUPPLEMENTARY EXPERT INTERVIEWS TO THE CASE STUDY RESEARCH

No. #	Positon/ Role	Description	Duration
10	Operations management/ service user	The company operates various refinery facilities around the world and is looking to leverage data-driven services to optimize operational processes	0:30 hours
11	Head of department/ service provider	The company develops various digital services for the automotive or manufacturing industry. The services range from predictive maintenance to the provision of specially developed IoT platforms	0:49 hours
12	Management/ Service provider	The company is an IT service provider that offers its customers data-driven services, e.g. for the preparation and analysis of data sets	0:33 hours
13	Management/ Service provider	Provision of data from, for example, production facilities and the development of the associated necessary IT infrastructure and software	0:30 hours
14	Innovation Manager / Business Consulting	Consulting for startups, SMEs and large companies regarding the development of digital services	1:07 hours
15	Project staff/ service user	Automotive supplier uses data-driven services to make decisions and optimize internal processes	0:42 hours
16	Innovation manager/ service provider	Lead innovative projects such as the development of data-driven services at a strategic level	0:49 hours

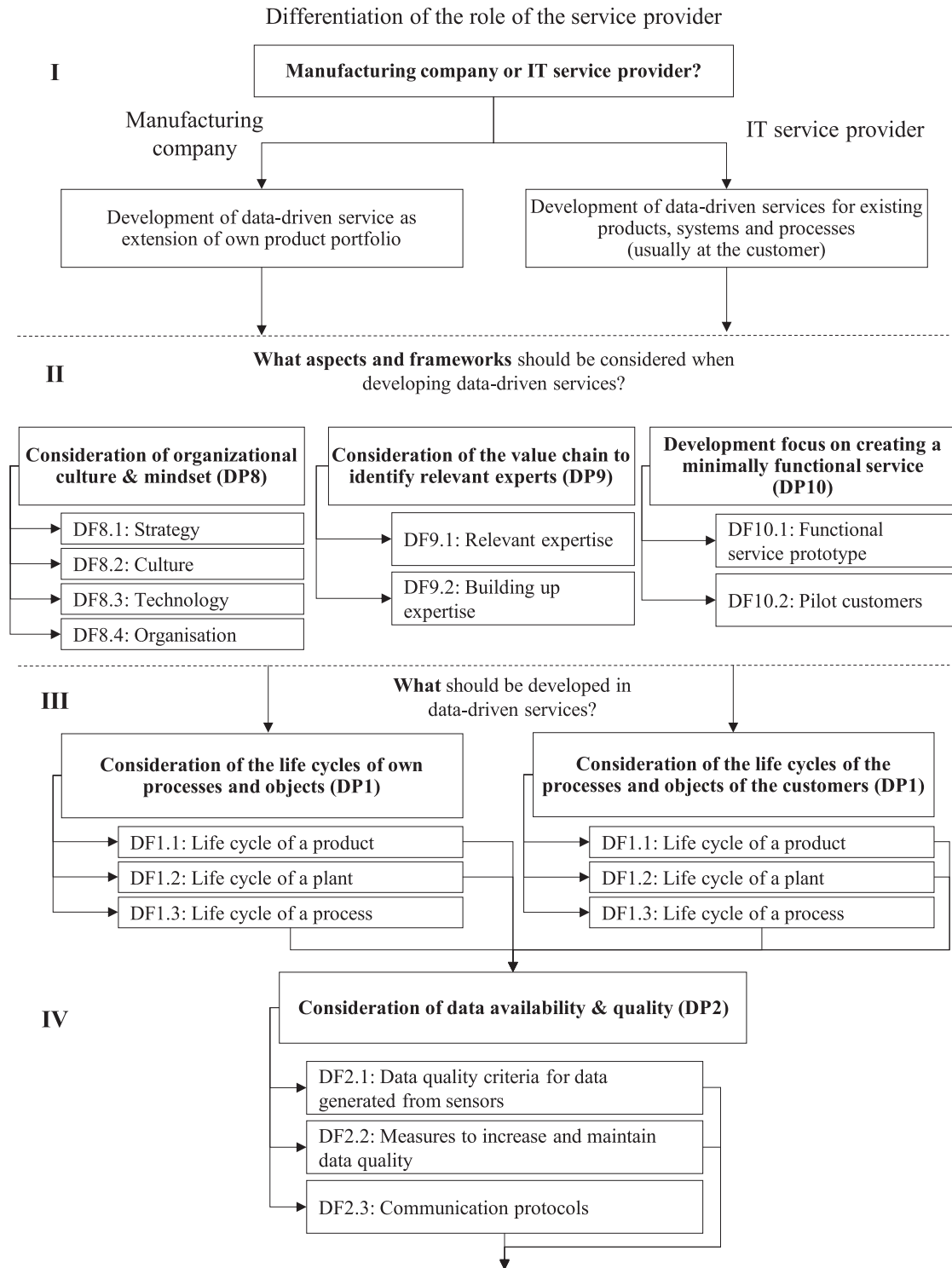


Fig. 4. Action guideline for the use of the design principles (1/2).

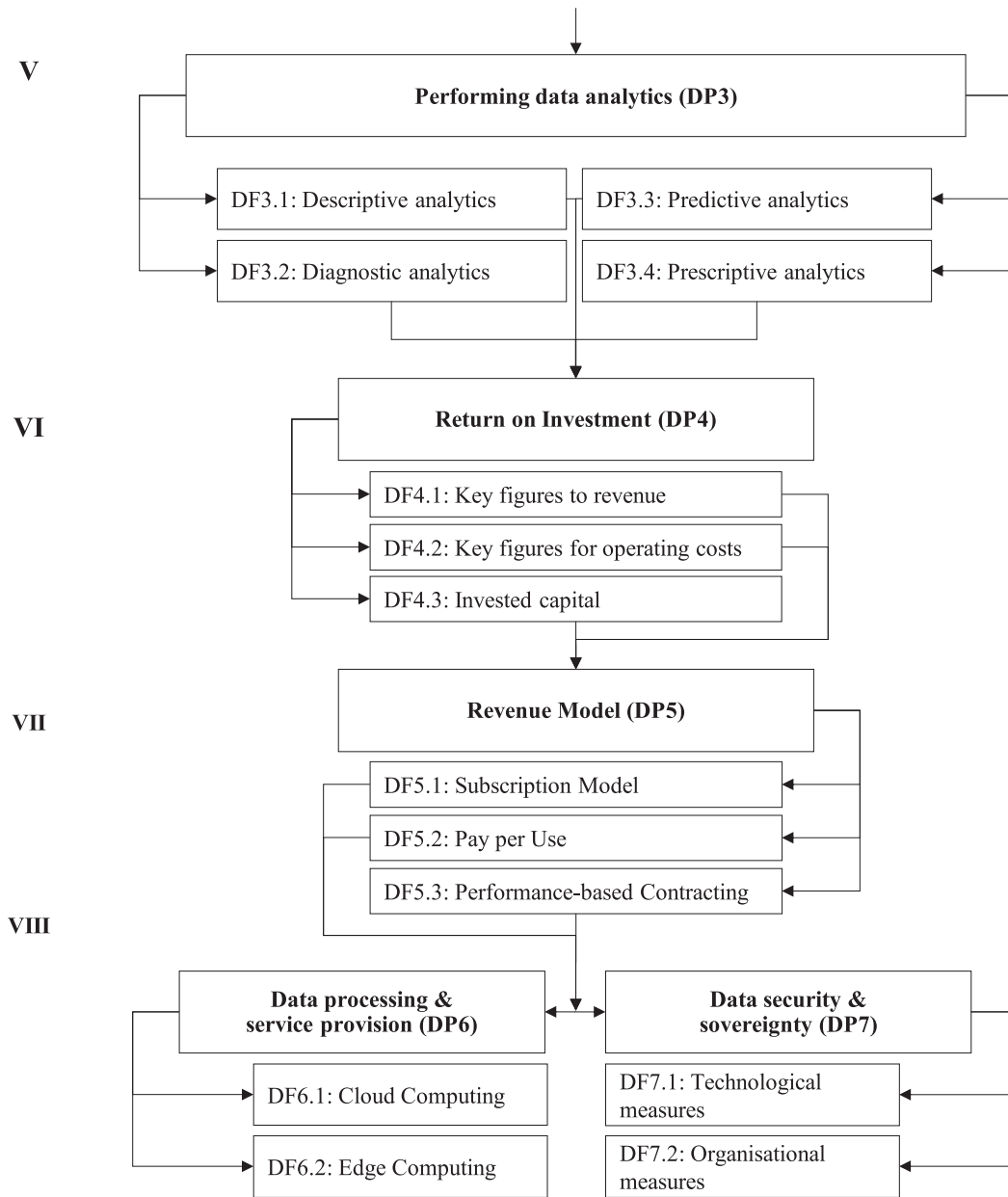


Fig. 5. Action guideline for the use of the design principles (2/2).

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