Understanding Data-Driven Product Service System characteristics: a conceptual framework for manufacturing applications

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Abstract: The explosion of digital technologies and data analytics capabilities are leading companies to rethink they offers and expand more than ever their business into the service domain. Specifically, considering manufacturers, the emerging possibility to connect products and create IoT architectures at the customer side, enable them to retrieve data flows during the products' lifecycle. Analyze those data opened opportunities to obtain information to use intra-organization and at the same time to enhance already existing service or to develop new ones. Even the potential of data availability in this context is recognized in the literature, further work is still needed, especially defining how these new data-driven offers should be engineered and structured. In this view, this study provides a comprehensive interpretation on the general key components and characteristics of those services, defined as Data-Driven Product Service Systems (DDPSS), aiming at supporting the comprehension of specific principles and consequently the systematic creation of DDPSS. Indeed, limited research is devoted to the definition of the unique characteristics of those services and common agreement is still missing. The paper developed a two-hierarchical conceptual framework describing DDPSS typologies is proposed. The framework value is twofold: first it categories and harmonizes service typologies into a structured model and second, it can be used as a support tool during the service design phase, since it can inspire and guide service development. In the end, the paper also presents an explorative application of the conceptual framework within a different manufacturing company. The applications show both the descriptive and the prescriptive nature of the model; indeed, it is used to analyses the current position and to propose new trajectories for the companies' service offering.

Keywords: Data-Driven, PSS, Smart Connected Product, Servitization

1.Introduction

In the last decade, two recent macro-phenomena and trends are specifically challenging the manufacturing strategies: Servitization and Digitalization (Frank, Mendes, Ayala, & Ghezzi, 2019). In particular, Servitization strategy consists in a transformation journey of product-centered firms towards product-service systems (PSS) (Kowalkowski, Gebauer, & Oliva, 2017). PSS has been defined as a bundle of integrated products and services that provides functionalities to customers and other stakeholders (Baines et al., 2007). In this wave, the implementation of advanced information and communication technologies (ICT) supported the enhancement of service offerings, both considering service delivery processes, management of service ecosystem, and the realization of digital PSS. By merging these two macro-phenomena, a new sub-stream of research has been derived, named 'Digital Servitization' (Vendrell-Herrero & Wilson, 2017). It is defined as the provision of "IT-enabled (i.e. digital) services relying on digital components embedded in physical products" (Schroeder & Kotlarsky, 2014). Digitalization enhances operations in a cost-efficient way and enables service quality through better resource allocation and more accurate information sharing inside and outside the boundaries of the firm. (Lerch & Gotsch, 2015; Vendrell-Herrero, Bustinza, Parry, & Georgantzis, 2016). Moreover, the recent development and adoption of new digital technologies like the Internet of thing (IoT), cyber-physical systems (CPS), have also intensified the development of smart, connected product (SCP) (Porter & Heppelmann, 2014). The result of such digitalization of products and infrastructures is enabling companies to offer *Smart PSS*, where the digital connectivity between components allows their autonomous interaction and the development of new functionalities. Consequently, product connectivity enables manufacturers to retrieve a large amount of data form SCP that, matched with effective data analytics tools, can become a key source of value creation (Rymaszewska, Helo, & Gunasekaran, 2017). In fact, collecting and elaborating data from the installed base has been recognized as a key aspect for manufacturers to servitize as it can enable sophisticated service offerings and new service-oriented business models (Adrodegari & Saccani, 2017). For instance, Kone, one of the largest global elevator companies, developed sophisticated condition monitoring and predictive maintenance services together with IBM. Both these services are based on the advanced elaboration of data gathered from the connected elevators. However, besides notable cases and several studies recognized the potential of data into the service domain, the understanding of how to effectively use information in enabling and supporting servitization is still limited (Cenamor, Rönnberg Sjödin, & Parida, 2017). Moreover, even some new streams of research are now emerging on "data-driven" services, a common agreement on the definition of what those services are is still missing and literature on this topic is widespread among different streams and disciplines. Authors agree on the fact that data-driven services rely on data streams, nevertheless, for some of them, they are linked to physical products as the main data source and complement them in a meaningful way (Kagermann et al., 2014). For others, they are detached form products and based on data such as customers' online behaviors recorded and used for strategic marketing planning and service management (Huang & Rust, 2013). Some others refer to "data-driven service" as a synonym of "Smart service" (Mittag, Rabe, Gradert, Kühn, & Dumitrescu, 2018; Anke, 2019).

In this context, where a limited research is devoted into the definition of the unique characteristics of those services (Klein, Biehl, & Friedli, 2018) and only fragmented knowledge on how to systematically develop them exist (Anke, 2019), this paper aims at giving a first attempt in the systematic definition of data-driven services and in the categorization od their relevant features.

1.1 Motivation and contribution

In this work, we will refer to data-driven services as "services which are characterized by a digital component and build on data from intelligent and connectable products. They create benefits for companies and/or customers through generation, collection, analysis and/or combination of internal and external data."(Kampker, Husmann, Jussen, & Laura, 2018). Specifically, the work defines the concept of Data-Driven Product Service Systems (DDPSSs) as a PSS solution, composed by a hardware part made of one or more SCPs, and including a service part which is based on data that the product and sensors at customer locations gather as the main data source. Moreover, a DDPSS implies the creation of a value stream through data exchange and analytics. According to the prementioned context, the authors argue that the first step to undertake in order to support DDPSSs understanding and development is the clarification of their peculiarity. Hunke & Engel, (2018) clearly stated the need to investigate data and analytics-based services in order to explain their key components. The identification of critical characteristics and the definition of a specific overview on those DDPSS would contribute first of all to the common understanding of the service solution and subsequently to the creation of them since it may help practitioners during the DDPSS design phase. Thus, the main objective of this paper is to investigate the key characteristics of DDPSS and to define a comprehensive vision of the possibilities that data collection at customer location and the utilization of analytic tools may create in a manufacturer offering towards servitization. With this aim, authors developed a conceptual framework that is representative of the DDPSSs characteristics. The framework can be used by companies as both descriptive and prescriptive tool. Indeed, it enable them to map their actual portfolio of DDPSSs and try to think about additional offers by looking into the spaces of the framework that are not cover yet.

The paper is structured as follow: Section 2 explains the methodology followed alongside the research, Section 3 discuss the framework, both clarifying how the dimensions have been defined and how they are related together. Section 4 is dedicated to the application of the framework. Section 5 concludes the research.

2.Methodology

The following steps have been undertaken to achieve the goal:

1.Literature analysis and identification of distinctive characteristics. As initial phase, a literature analysis has been fundamental to understand the current state of the art and to identify main gaps into the smart service, data-driven service and PSS topic. As already emerged, the need to reach a common view and understanding of the DDPSS phenomena is clearly stated (Hunke & Engel, 2018). With this purpose, during the literature analysis, attentions have been focused on recurrent o critical characteristics of those DDPSSs. Those characteristics have been subsequently organized into four dimensions.

2.Conceptual framework. All the considerations regarding the dimensions and their relationships have been transferred in a two-hierarchical conceptual framework. A conceptual framework has been chosen as the best way to develop our scope since it presents an integrated way of looking at a problem or a phenomenon (Levering, 2002), describing the relationship between the main concepts that emerge. The conceptual framework can be defined as a construct in which each concept plays an integral role. (Jabareen, 2009). Indeed, it "*lays out the key factors, constructs, or variables, and presumes relationships among them*" (Miles & Huberman, 1994), and it provides an understanding of a phenomenon through the interpretation of intentions. We accordingly developed both a narrative and a graphical representation of DDPSS, for showing the key dimensions that concur in the service provider and the relationships between them.

3.Application. The framework has finally been used in the context of a real case study, to show how it is possible to describe the DDPSS and to hypothesize a possible path to enhance the actual offer.

3.The conceptual framework

Based on existing relevant literature analysis, different characteristics of DDPSS have been identified that authors categorized into four dimensions that will compose the first hierarchy of the framework. To the best of our knowledge, similar works have been already performed with a different focus. A conceptual framework has been proposed to explain the convergence of Servitization and digital transformation of product firm, resulting in nine different possibilities matching three incremental levels of digitalization and three service typologies: i.e. smoothing services, (ii) adapting services and (iii) substituting. (Frank et al., 2019). Another research presented a data-driven business model framework,

considering six key dimensions that are commonly found, among various authors, in the business model domain. (Hartmann, Zaki, Feldmann, & Neely, 2016). Nevertheless, none of them represents the possible configuration and characteristics that the DDPSS should have.
Following paragraphs present and explain the four dimensions that have been proposed as the pillars of the conceptual framework, that are: *(1) Data Source (2) Data Visibility, (3) Response type and (4) Decision Ownership*. The dimensions have been also characterized considering different options that the single dimension allows. Thus, for each dimension, the different characterization has been also reported and explained.

3.1 Data source

As already stated by Porter & Heppelmann, 2014, the capabilities of SCP are expanding industry boundaries. Manufacturers are more and more moving into a domain where, in addition to data coming from the machinery, other data may be gathered both on a machinery level but also at a process level, such as efficiency and productivity parameters, utilization, quality of the production and so on. (Sambit, Vinit, & Joakim, 2016; Rymaszewska et al., 2017a). This not only means the competition shifts "from discrete products to product systems consisting of closely related products, to systems of systems that link an array of product systems together" (Porter & Heppelmann, 2014) but also that the service may reach those scopes. The manufacturer has the possibility to continuous auditing of customer operations (Sambit et al., 2016; Coreynen, Matthyssens, & Van Bockhaven, 2017) and expands value creation operating within the field of product use (Rymaszewska et al., 2017). "Data source" emerges as a crucial dimension to consider, which identifies available or potentially available data, to be integrated into the service offered by the manufacturing company. Some data categorization already exists in the literature, that tried to formalize and give order to all possible data sources. The one proposed by Hartmann et al., (2016) is specifically oriented to the service domain. Nevertheless, these classifications remain focused on data provenience and not directly linked to the possibility to exploit those data in the context of service. We decided, instead, to limit the scope to those data that reflect the possible service offerings and that may impact the design of a new service at a customer side. Accordingly, we defined four different data-categories that influence the scope of the service that a service provider can offer: *(i) Product data, (ii) System data, (iii) Enterprise data* and *(iv) External data*. Depending on the product specification, the meaning of the different categories may slightly vary. Indeed, what product means depend with respect to the manufacturing company and it can go from component to machinery or a complete production line. In the same way, all the other categories could change in their meaning. Nevertheless, besides different "product categories" exist, the levels are applicable to all product typologies. Categories are defined as follows:
Product. Data are related to product identity, such as serial number, location, provenience, technical features, age. In this category data related to the product heat status are also included.
System. Data regarding the system in which the product is primarily included or embedded product functionality.
Enterprise. Data gathered thanks to the integration of additional sensors or sources within the customer ecosystem, which is the environment in which the product works, such as production scheduling, orders status, etc.
External. Data are retrieved from a different source of knowledge, open and always available, which can be related to the external environment.

3.2 Data visibility

Data sharing has been recognized as a key point in the provision of DDPSS, indeed the exchange of data has always represented a possibility for a high level of customization, configuration and implementation of solutions (Sambit et al., 2016). Some authors also explain the need to convince customers to effectively share their data through the clarification and assessment of value creation (Ostrom, Parasuraman, Bowen, Patrício, & Voss, 2015; Rymaszewska et al., 2017a). "Data visibility" dimension represents in this work the level of visibility on data from different actors. Three different categories of data visualization have been defined. They include the possibilities in which the customer can only have access to his data, the customer shares the data with the service provider or data are shared also with actors from outside the firm's boundaries, that will be called generally "third parties". Third parties may have the knowledge and expertise based on a larger sample. Moreover, they can own different data in terms of category and thus offer a completely new service. The participation of a 3rd party in the network may offer opportunities regarding access and sharing of resources, including knowledge and capabilities (Loukis, Kyriakou, Pazalos, & Popa, 2017). This dimension directly influences service typology and data analytics opportunities since different actors may be enabled to exploit data and deliver services (Sklyar, Kowalkowski, Tronvoll, & Sörhammar, 2019). The differences between the three categories are explained below.
Customer. Data are visible only to the customer. A lot of times, the customer uses just a little part of those data and it is not able to transform them in useful information. The customer may choose to send and display data to the service provider.
Customer and Service provider. Data are visible to the customer and the service provider (manufacturer) can access customers data constantly. The product owner can leverage data from a lot of his products at different customer locations and over time increase his knowledge and expertise based on different experiences.
Customer, service provider and 3rd party. Data are visible to the customer, service provider but also to other parties. Those other parties may have knowledge or skills that the manufacturer does not have. They may also own different dataset, both in terms of quantity and source type. Those data may enrich the dataset of the manufacturer and enable the provision of new DDPSS.

3.3 Response type

Data availability has always played a central role in facilitating analysis of a situation and make the best decisions and data science and analytics, for their nature, have the goal of improving decision making. Having access to data, data elaboration and information facilitate the analysis of a situation and lead to best decisions (Provost & Fawcett, 2013). "Response type" dimension has been proposed to describe the output of the data analytic phase. Two different possibilities may emerge, which are (1) an automatic response from the product to a specific input, which requires a stream of data that are not shown to an operator, or (2) an analysis of data that is provided to a human user. For what concern the possibility of a product to reasoning and act, different levels of intelligence have been found in the literature (Kiritsis, 2011), and they all refer to the functionality that the product embed and related literature deal with smart product topic. Nevertheless, data gathering allows developing service based on data analytics aimed at interacting with a human in order to inform and support him/her in the decision-making process. The two categories are better defined and exemplified as follow:

Autonomous reaction. The product has embedded intelligence through which is able to autonomously react at a simple event and more sophisticated situation (Kiritsis, 2011). For example, a simple intelligent mechanism can be seen in the thermostat applications which allow the refrigerator to modify temperature according to the external one. Sophisticated reactions are for examples ETS systems of the car. The car can adapt the trajectory in accordance with road conditions.

Data supports human decision making. The decisions to be taken on data are more complicated and subjective to difficult reasoning and expert interpretation. Data can be transferred as raw data or elaborated at the product level and then transmitted to a Human Machine Interface, that can be a PC, a web platform or other devices. Data are used to support the decision-making process at different levels, from the operational to the strategical one, rather than enable automatic response. For example, a well-known ice-cream machinery producer offers analytics services able to support both operators in the efficient use of the machinery and the production planning decisions providing machinery parameters, ice-cream consumption trends and weather forecast.

3.4 Decision ownership

The level of interaction and responsibility of different actors along the decision-making process may change and can reach the final step where a decision is made, so that an activity is outsourced and delivered as a service from the DDPSS provider. Outsourcing activities or whole processes to the service provider have always represented one of the service businesses, and digital services can contribute to it. (Urmetzer, Neely, & Martinez, 2017; Frank et al., 2019). In this work, the "decision ownership" dimension has been included to identify who perform the decision. Particularly, this dimension defines if service providers are adopting a passive or proactive strategy towards service provisions and define who is responsible for the decisions and assumes the risk of it. Four different categories have been defined, that represent the possible actors who can act based on the information provided by the system. The product itself has been included in the categories since when the response mechanisms are autonomous, the product is responsible for the decision.

Product. When embedded logics are performed, the product itself act to perform a decision that has been already settled in its memory. When there are not embedded logics, data analytics is a part of the decision process and different actors can perform decisions.

Customer. The customer decides what to do, with respect to the data or information provided by the PSS provider.

Service provider. The service provider decides what to do on the basis or real-time data stream that enable him to take actions when is needed.

3rd party. Other service providers oversee the decision, again considering the data-stream on which they should have the visibility.

3.5. Interaction between dimensions

Considering the different dimensions and categories previously defined, several DDPSS typologies can be depicted. Figure **1** graphically represents how the different dimensions interact and create the framework. As it is possible to notice, *Data Source* is represented on the Z-axis, while *Data Visibility, Response type* and *Decision Ownership* lie on the same plane XY. *Data source* represents an independent dimension, that creates three layers, that are representative of different purposes of the service.

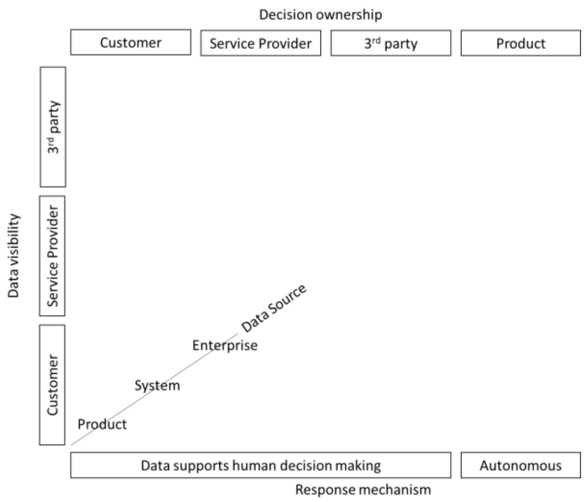

Figure 1 DDPSS characteristics framework

The interaction of the other three dimensions, instead, create different services typologies and values for the customer that are identical for each of the three layers. Service scope is defined in the framework according to three of the dimension categories: "Product", "System" and "Enterprise". "External data" has not been included as a different layer, since it is always available in addition to other data. For each service scope, the other three dimensions interact together as represented on the XY plane. As it is possible to notice, the *Response mechanism* dimension limits the *decision ownership,* in the case of an autonomous reaction, since the only category allowed in the decision ownership is the "product". All the other combination in the framework are possible.

4. Application case

Alpha is a multinational company leader in electrification products, robotics and motion, industrial automation and power grids, serving customers in utilities, industry and transport. The company has undertaken a digital transformation program that, starting from the introduction of connectivity and the creation of a cloud-based platform, is leading to the development of new services based on this continuous data flow. Even though the project embraces most of the products of the company, the case study is based on a specific product i.e. low voltage circuit breaker (CB). In the case study, the presented framework has been used to first analyse the DDPSS that are now available for those product typologies (AS-IS state) and consequently to present some possible option to create new services (TO-BE state). Considering this company, "Data source" dimension has been firstly examined and defined. Each category is explained in Table 1. Column one also reported AS-IS or TO-BE, considering respectively if the company is already gathering those data category or may gather them to reach advanced offers. For each of the different data source levels, all the offers have been analysed following the other three dimensions. Figure 2**Error! Reference source not found.** represents the framework, that depicts in green the AS-IS state, and in blue some ideas for the TO-BE state. Different textures have been used to symbolize the different "Data source", as reported in the legend. Numbers represent different offers that are described below. First DDPSSs have been focused on the product layer, on which the company is traditionally oriented. Data are automatically analysed in order to apply simple reaction that enables the product, for example, to adjust settings (1) or coordinate with other product to efficiently use power supply resources (2). Those capabilities are provided as embedded functionalities and are based on thresholds that are defined by each customer, in accordance with his need. Another step has been done by the company providing the possibility to connect the CB to a cloud-based platform and to retrieve data from the product. Data collected includes both "product data" and "system data" which is, in this case, the electrical one.

Even not all the time the access to data is given to the company, the platform provides analytics tools that analyse both the product health status (3) and the energy consumption (4). Those services include real-time alarms based on thresholds and analogic input and descriptive analysis to the customer who should interpret information and autonomously decide what to do. Indeed, no decision are overseeing by the service provider or other actors. In order to be able to give prescriptive and personalized information to the customers, data need to be visualized form the company moving offers on the second level of "Data Visualization" axis. In the AS-IS state, the company is not allowed from all the customer to access their data or a part of them, limiting the possibility for the company to offer DDPSS but also to internally analyses data to define and implement possible improvements. In the TO-BE state, the company is supposed to own data from a lot of his products at a different customer location. This will enable the company to analyses how devices are used and how they operate/function in different environments and to use the information both for new offerings and for the internal organization.

Table 1: Alpha "data source" definition

Category	Description
Product **(AS-IS, TO-BE)**	Data are related to product identity, such as serial number, location, provenience, technical features, age. In this category data related to the product heat status are also included, such as contact wear, the number of operations and so on.
System **(AS-IS, TO-BE)**	The system is represented in this case in the energy system and comprehends all the energy flows as well as energy quality parameters. A CB is able to gather data on energy consumption and conveying all the energy flows into a single platform enable the service provider to collect data on the whole energy consumption of a factory.
Enterprise **(TO-BE)**	Enterprise data may represent data related to the customer production processes, both considering data on machinery efficiency, quality of the final product, machine parameters, operators and so on. Data on energy contracts of the company may be also considered.
External. **(AS-IS, TO-BE)**	Interesting external data, in this case, are weather data, that can impact both on the energy consumption and on the decision related to the installation of renewable sources. Regulations and certificates for all the different region in which the service may be deployed represent another external information to be collected and considered. Energy prices can be also included in this category in the case energy is purchased form open energy markets.

For example, the company may analyse different alarms for different CB and suggest changes in the electrical plant or discover critical loads that cause problems (5). Maintenance operators may directly contact the customer to propose maintenance activities (5), without the need that the customer monitors or understand specific machinery parameters. Moreover, in the AS-IS state, the company does not give the possibility to other companies to use data in order to offer additional services. Some sporadic cooperation has been done with other entities, but not yet considering the possibility to give them freedom on the services. A step forward in the TO-BE state can be made from the service provider deciding to partner or open the platform to other actors. This will allow companies to use this data to offer complementary service. For example, considering only product data, the supplier of consumables may offer a forecast of the needed quantities according to the usage (6), and at the same time, he can use it to plan his production. To move left in the framework, the company should approach service provision proactively and thus, after data are analysed, act for the customer who completely delegates some activities to him. Moreover, if other actors are involved in the service provision, they can directly take the responsibility for the service. For example, again considering product data, if the manufacturer is now able to define when maintenance is needed and there is an agreement with the customer, he should act proactively to offer the service (7). In the same way, the consumable provider may manage the direct provision of consumable on customer need (8). This step not only requires the need of data visibility from the party that should deliver the service, but also a structured back-office and resources that are able to monitor, interpret information and perform a proactive service in an efficient and timely way. Another consideration to enlarging service portfolio and the solution itself is on the data source dimension. Indeed, the actual offer considers data coming from the product and system, with the integration of some external data.

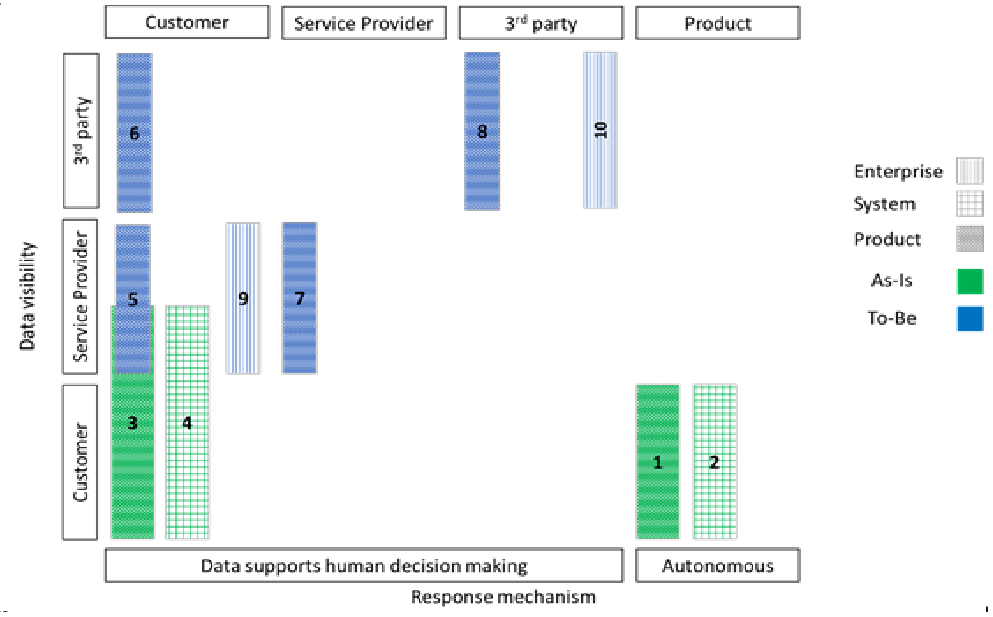

Figure 2 Alpha DDPSS offering - AS IS vs TO BE

Nevertheless, a lot of times those data are not enough to provide interesting insight, considering that many data are independent between them. In this view, the company may work to give the possibility to customers to connect and integrate enterprise data, that may be for example the ones regarding production, quality, energy prices or space occupancy. This would allow the manufacturer to expand the service scope and ideally move towards different service levels as described above. Considering the complete set of information available, the company may reach a complete understanding of the customer and may be able to reach more value-added offerings. For example, it may be able to offer optimization algorithms to suggest to the customer the best wat to plan production limiting the energy expenditure (9). Considering, instead, 3rd parties, one possible service that is suited is the one of energy trading (10). In the same way, those new services have been proposed, it is possible to proceed forward and try to cover all the blank space in the graph.

The application in company Alpha shows the application of the framework both in the descriptive and the prescriptive nature of the model. Indeed, it is used to analyses the current position and to propose new trajectories for the companies' service offering. The application shows how all the digital and data-driven offer of the company can be represented by mean of the framework and it also can support the company in order to start thinking at different offers to expand their portfolio.

5. Conclusion

The presented work contributes to the definition of how data streams, enabled by SCP, may support and enhance the servitization path of manufacturing firms. The paper is focused on the DDPSS domain, and analysing relevant paper in the context, proposes a conceptual framework that represents a first attempt towards the harmonization of literature in the topic, and organization of DDPSS typology, by mean of an analysis of characteristics that are comprehensively represented and organized. Indeed, it proposes four interesting dimensions that are summarized into a two-hierarchy conceptual framework that starting from the characteristics of solutions, is able to represent solution typologies. The framework represents a useful tool in two directions: on one side to contextualise the actual situation of companies and on the other it can be used with a prescriptive approach, looking at the possible areas that are not covered yet. With this perspective, the framework is also a contribution to future DDPSS development, since the clarification of their key aspects is a compulsory step for their development. In the paper, an application case has also presented to demonstrate the effective ability of the framework to describe a current situation and be a starting point to develop new solutions. The framework considers characteristics that are related to the specific domain of data included in the service offering, while it does not take into consideration either technologies that enable the realization of the DDPSS and the business models that may be used to reach the customer or feasibility analysis. Indeed, the technological decision may limit the possibility to explore some of the levels of the presented offer, and on the other side, the same technologies may enable manufacturers to introduce innovative business models. Indeed, the possibility to monitoring the real status of products, take action for the customer and provide prescriptive analytics enable DDPSS provider to also rethink the way they reach the customer, supporting, for example, pay-per-use contracts or payment on cost-saving and so on. Concluding, the framework has been shown in action in the paper with a single case study, a natural extension of the work could be the employment of the framework in different manufacturing domains in order to reach a subsistent validation of the tool.

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