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Functional and Structural Roles of Data in Service Ecosystems

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Abstract

Data play an increasingly important role in today's service ecosystems, where actors integrate resources to create value at different levels of aggregation (micro, meso, macro). To advance our understanding of the role of data in such contemporary data-rich service ecosystems, we draw on the service-dominant (S-D) logic and data ecosystem literature. Extending the current understanding of data in the literature, we demonstrate how data and data ecosystems have become intertwined with service ecosystems and how data as a meta-resource connects actors, enhances systemic visibility, and drives innovation in these ecosystems.

Keywords: service ecosystems, service-dominant (S-D) logic, data, data ecosystems, conceptual research

1. Introduction

Data are often described as the "oil of the 21st century," as they are regarded as critical success factors for businesses across industries (Davenport, 2014; Kitchin, 2014). Ongoing digitalization and newly available data sources enable businesses to access a vast amount of diverse data. Furthermore, technological advancements and evolving algorithmic intelligence provide novel opportunities to make sense of raw data, accelerating value creation and innovation for organizations.

However, previous research indicates that organizations often face difficulties adapting their practices to maximize the value of newly accessible data sources (Sivarajah et al., 2017). As a result, many organizations are still "digitally immature" because they lack the capability to harness data for value creation (Brinch et al., 2021). Some have argued that this is at least partly due to an inadequate theoretical understanding of the role of data in service ecosystems (Otto, 2015).

Before proceeding, it makes sense to define what we mean by data, given data is an often-debated concept. Data, information, and even knowledge are interrelated concepts that are often used interchangeably. Understanding the dynamics within and between these concepts is necessary to comprehend how data contribute to knowledge, which is used to integrate resources and create value. On the other hand, knowledge drives us to collect specific information and data from the surrounding environment (Ackoff, 1989; Tuomi, 1999).

Data are typically described as objective facts or observations (Rowley, 2006) or symbols representing particular properties and qualities of objects, events, and environments (Ackoff, 1989). Moreover, big data refers to data sets that are large in "volume, variety, velocity, and/or variability that require a scalable architecture for efficient storage, manipulation, and analysis" (National Institute of Standards and Technology, 2015 p. 5). Big data flows, varies and expands continuously with the world and the objects that it represents. Due to its dynamic and expanding nature, big data is considered one of the most significant disruptions affecting contemporary ecosystems (Agarwal & Dhar, 2014).

Data are traditionally considered information and knowledge when structured and processed by humans (Ackoff, 1989). However, recent technological advancements, particularly artificial intelligence (AI), indicate that the role of data in autonomous and automatic decision making increases (Jennex, 2017), thereby altering the traditional hierarchies associated with data and knowledge as resources.

This conceptual paper is motivated by the identified lack of knowledge of the role and properties of data and related processes in service ecosystems. We employ the service-dominant (S-D) logic (Vargo & Lusch, 2004, 2008, 2016) as a lens to understand service ecosystems as "relatively self-contained self-adjusting systems of resource-integrating actors connected by shared institutional logics and mutual value creation through service exchange" (Vargo & Akaka, 2012, p. 207). While the view of S-D logic emphasizes the importance of resources and resource integration in service exchange and value co-creation that is, resources play a fundamental role in service ecosystems, little research has been conducted on the role of resources from a systemic perspective (Huhtala, 2022).

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Data and related practices and processes in service ecosystems involve multiple actors. Their expectations of data's role in value creation are crucial to the strategic use of data-related resources. Furthermore, the growing importance of data in contemporary society necessitates a better understanding of how data as an emerging resource shapes not only the outcome of value creation but also the functioning of service ecosystems. We argue that a deeper understanding of the properties of data as a resource in service ecosystems is required.

To this end, this paper investigates how data functions in and shapes interconnected and interdependent service ecosystems in which service exchange occurs in various contextual settings involving multiple actors (Vargo & Lusch, 2004, 2008, 2016). Specifically, we aim to answer the following research question: *What types of functional and structural characteristics are related to data as a resource in service ecosystems?* To better understand how actors form their views on data's role in value creation, we apply S-D logic and the existing literature on the role of resources in value creation at multiple aggregation levels (micro, meso, and macro).

The paper continues as follows. The second section provides an overview of resources in service ecosystems. In Section 3, we discuss the defining characteristics (i.e., functional and structural roles) of the data identified from the literature. In Section 4, we elaborate on the role of data and present the following three propositions for understanding and studying data in service ecosystems: P1. Data as a resource *connects actors and shapes institutions* in service ecosystems. P2. Data as a resource *enhances systemic visibility and drives innovation*. P3. Data have become a *dynamic meta-resource embedded in all levels of aggregation in service ecosystems*. Thus, we contribute to the ongoing discussion of actors' resource integration and value co-creation efforts as well as the role of data in facilitating these. Before concluding, we discuss the implications for research and practice.

2. Resources in service ecosystems

S-D logic was introduced by Vargo and Lusch (2004, 2008, 2016) to focus on the essentiality of service, referring to the application of resources for the benefit of others as the basis of all exchange and value co-creation in service ecosystems. Service is defined in S-D logic in terms of applied resources that can be "anything, tangible or intangible, internal or external, operand or operant, that the actor can draw on for increased viability" (Vargo & Lusch, 2014, p. 121). Various types of resources are regarded as fundamental components of service ecosystems wherein actors integrate resources to co-create value.

In S-D logic, all social and economic actors can be considered resource integrators (Vargo & Lusch, 2008). Actors are responsible for coordinating the service exchange and shaping systemic structures by forming relationships with other actors and determining the optimal value of resources in their respective contexts. Institutional rules (e.g., values, norms, and regulations) guide what constitutes a valuable resource in each interaction and how such resources can be accessed, adapted, and incorporated into each particular context (Vargo et al., 2017).

Due to digitization, the operational environment in which resources are integrated to create value has changed drastically. According to Amit and Han (2017), digitization has widened the range of resources available to businesses, enabling them to conceive of and design novel configurations of resources and value creation with a broader array of stakeholders. The authors proposed that organizations and their resource configurations within service ecosystems should view digitization as a crucial "contextual element." In this context, data, especially big data, can be viewed as a new type of resource with new functions. Its central position in contemporary ecosystems necessitates a greater understanding of its role and properties.

2.1. Types of resources and their functions in resource integration

S-D logic distinguishes two types of resources: operand, which are static and require action to be performed on them before they can provide value (e.g., natural resources), and operant, which are capable of acting on other resources to contribute to value creation (e.g., human skills and knowledge) (Vargo & Lusch, 2004). The service-for-service exchange in service ecosystems is driven by the integration of resources, and their application, guided by operant resources (Vargo & Lusch, 2004). In fact, actors themselves are considered operant resources because they apply their resources to provide services for other actors to co-create value (Vargo & Lusch, 2014, p. 119). Furthermore, as the concept of operant resources has evolved and its conceptualization has expanded, it has been argued that technology combined with an increase in data has the potential to act as an operant resource (Akaka et al., 2014).

According to S-D logic, resources are abstractions, meaning that a "resource is a function that the substance contributes in order to achieve a desired end" (Vargo & Lusch, 2014, p. 121). Vargo and Lusch (2014) highlight the significance of human evaluation and action in determining "resourceness," which refers to the quality and realization of potential resources, i.e., their usefulness. As an operant resource, human knowledge

is often cited as crucial to the development of resourceness. This application of operand resources through operant resources implies that resources evolve. The human-centricity that has traditionally been central to the S-D logic approach is exemplified by the notion that the growth of resources is generally related to the history of human civilization, the expansion of human knowledge and skills, and the accumulation of potential resources. Therefore, much innovation is about enhanced resourceness (Vargo & Lusch, 2014).

In summary, organizational resources may originate from various sources, serve various market-driven functions, and evolve based on market needs and the accumulation of knowledge or skills, whether human-or technology-driven. This is also the case with data, as virtually every modern action leaves digital traces that can be tracked. The data may be obtained from internal or external sources or through tracing transactions. The most recent technological developments, such as connected devices and machines, the application of sensors, and the production of (user-generated) online content, allow service ecosystems to collect, process, and use an ever-increasing volume of data from multiple sources (Niebel et al., 2019).

2.2. Structural view of resources and resource integration

Due to the systemic nature of S-D logic, resources exist, and the enhancement of resourceness and resource integration occurs at multiple structural levels. First, resources are obtained from various levels of the system, such as private sources (e.g., self, colleagues), market-facing sources (e.g., from other collectives via exchange), and public sources (i.e., collective access from communal sources). In the provision of services, the joint integration of resources occurs across multiple actors, employing resources from numerous sources (Vargo & Lusch, 2004). Second, according to S-D logic, actors can represent many types of units that operate at various service ecosystem levels. Vargo et al. (2008) suggest that individuals, groups, organizations, businesses, and governments can be categorized as service systems if they act, apply resources, and collaborate with others for mutual benefit. This indicates that actors from multiple levels of ecosystems engage in the interaction, application, integration, and exchange of resources. Moreover, these processes occur at the micro (e.g., between individual actors), meso (e.g., organizations or other collectives), and macro levels (e.g., national economies) (Akaka et al., 2014; Vargo & Lusch, 2008). Lastly, institutions that govern interactions and resource integration exist, evolve, and emerge on multiple ecosystem levels (Chandler & Vargo, 2011).

Hunt and Morgan (1995) explained how markets emerge when actors seek access to resources and consequently interact to gain such access. Applying the S-D logic ecosystems lens enables a new understanding of data as a resource in networked and multilevel systems as the logic perceives resources as accessible by multiple actors operating on multiple levels. However, not all resources are accessible because, as Vargo and Lusch (2014) note, there are resources (private or public) that are not available or meant for exchange due to existing social institutions, such as rules, norms, meanings, symbols, and practices. Moreover, some actors are unwilling to exchange their resources with other actors (Vargo & Lusch, 2014). These institutions are in a constant state of flux, shaped by interactions within the system and the operating environment in general.

The ecosystems approach emphasizes the need to consider micro, meso, and macro perspectives of resource integration and calls attention to institutions that guide interactions between actors at various levels (Chandler & Vargo, 2011). In this paper, we adopt this structural view of resource integration and explore how data as a resource exist and can be integrated at different systemic levels, namely, micro, meso, and macro levels.

3. Defining characteristics of data in service ecosystems

Since 1980, when the concept of "data resource management" was established, data as a resource for businesses has been a subject of research (Goodhue et al., 1988). The resource-based view of data was founded on the general premise that for an organization to manage any resource effectively, its role and properties must be understood (Levitin & Redman, 1998, p. 90).

In the resource-based literature, data resources are typically distinguished from other types of organizational resources (Levitin & Redman, 1998; Mamonov & Triantoro, 2018). Data are shareable and can be used simultaneously by multiple actors; they are copyable at low cost, transportable efficiently with almost no delay, non-fungible as data items are unique, versatile for use in a variety of contexts, depreciable as it is often time-sensitive, and renewable as new data can be collected and analyzed continuously (Levitin & Redman, 1998).

Levitin and Redman (1998) refer to data as the “meta-resource” because it is vital for the management of other resources and directs their utilization. Recent research on innovation and service development often employs the term “data-driven” (Luo, 2022; Zambetti et al., 2021), referring to the ability of data to drive processes and influence institutions.

As presented in Section 2, the classical categorization of resources in S-D logic distinguishes resources into operand and operant. Huhtala (2022) suggests that data can be understood as both. Data function as an operand resource in value creation when integrated with other operant resources, such as the organizational competences to collect and analyze data (Lim et al., 2018). However, data also influences and directs the use of other organizational resources (Levitin & Redman, 1998), making it an operant resource (Huhtala, 2022). Xie et al. (2016) acknowledge the cooperative role of data in promoting value creation by interconnecting firms and customers, which further suggests that data has dynamic capabilities in shaping the components of the service ecosystem.

Huhtala (2022, pp. 39–40) presented five main categories in which data can yield value recognized by contemporary data literature: 1) *recognition of new opportunities* (Saarijärvi et al., 2014), 2) *improved decision making* (Davenport, 2014), 3) *improved products and services* (Davenport, 2014), 4) *cost reduction* (Davenport, 2014), and 5) *operation optimization* (Lavalle et al., 2011). The wide variety of identified value categories suggests that data as a resource are often involved in value creation and service exchange in contemporary markets.

Although there is broad consensus on the significance of data's role in value creation, most literature on the use of data in service development continues to view data solely from the service provider's perspective. Huhtala (2022) calls for a better understanding of data as a resource for multiple actors. This is particularly pertinent, as digitalization drives widespread connectivity, thereby blurring previously strict actor roles (Storbacka, 2019). Addressing the identified gaps, the functional and structural roles of data are discussed on a systemic level and through the lens of S-D logic in the following two subsections.

3.1. Functional characteristics of data as a resource

Based on the emerging literature on the function of data in value creation and innovation, we first investigated the functional roles of data in service ecosystems. Three functional roles are proposed: data connecting actors, data enhancing systemic visibility, and data driving innovation. The introduction of these roles represents the first attempt to investigate how data functions in service ecosystems and consequently influences ecosystem functionality.

3.1.1. Data as a resource connecting actors. Applying S-D logic (Vargo & Lusch, 2004, 2008, 2016) enables data to be viewed as a resource in networked ecosystems. S-D logic views resources as accessible to multiple actors and considers the actors themselves operant resources in providing service to other actors for mutual value creation (Vargo & Lusch, 2014). Actors interact to gain access to resources (Hunt & Morgan, 1995). "Resources thus connect actors to one another (and vice versa) and are valuable because of this" (Chandler & Vargo, 2011, p. 37). On the other hand, connected actors collectively impact the "expansion and contraction" of resources (Constantin & Lusch, 1994).

Lim et al. (2018) discuss customer data, in particular, facilitating the relationship between a firm and its customers. For example, automobile manufacturers collect data via sensors to assist drivers by providing them with helpful information, such as fuel consumption, safety, and navigation (Lim et al., 2018). Therefore, according to Lim et al. (2018), data are critical for understanding and attracting customers, as well as for improving service provider operations. Customer data can also improve customer loyalty because it enables more precise targeting and more profound customer insights and facilitates customers' value creation (Saarijärvi et al., 2014). Therefore, data not only establishes connections between various actors but also maintains them by fostering mutual dependencies.

Xie et al. (2016) demonstrate how big data interconnects firms and customers in promoting value co-creation. Depending on the role of the customer, big data resources create value through transactional, communicational, participative, or transboundary process (Xie et al., 2016). Based on these empirical findings, the authors named big data resources "cooperative assets" that can create value for both the customer and the firm.

The interconnected nature of data at the system level is also reflected in so-called data ecosystems, defined as "a loose set of interacting actors that directly or indirectly consume, produce, or provide data and other related resources" (Oliveira et al., 2019, p. 16). According to a literature review by Oliveira et al. (2019), data ecosystems are often characterized by a circular flow of resources, sustainability, demand that encourages supply, and the development of actor dependence. Applying S-D logic to data ecosystems makes it apparent that these ecosystems facilitate the formation and maintenance of connections (i.e., relationships) between actors, as they can access resources they do not own or control unilaterally. In these ecosystems, actors become interconnected due to data exchange or shared investment in data infrastructures. The actors also remain connected because they share access to a resource with mutual interest. Alaimo et al. (2020) argue that in the digital economy, business relationships and connections are

primarily based on data. Consequently, services exchanged across platforms are essentially "data relations" (Alaimo et al., 2020).

Data-sharing ecosystems emerge "when organizations agree to share data and insights under locally applicable regulations to create new value for all participants" (Capgemini Research, 2021, p. 1). Capgemini (2021) estimates that in the next five years, data ecosystems have the potential to save businesses up to 9 percent of their annual revenue due to new revenue streams, cost savings, and productivity improvements. Due to this potential, many organizations have recently established data ecosystem initiatives to form connections (i.e., partnerships) with other actors who share their interests. For example, in 2020, the Mayo Clinic, a provider of integrated healthcare services, education, and research in the United States (US), launched the Clinical Data Analytics platform. The platform is designed to share data and assist collaborators in solving complex medical problems (Mayo Clinic, 2020).

Increased connectivity, such as sensor data collected by the Internet of Things (IoT) and user-generated content data collected from communication platforms, is here to stay (Davenport, 2014). Thus, we conclude that, to realize the vast amount of data available, organizations must recognize and build partnerships to harness the connective potential of data and available data sources.

3.1.2. Data as a resource enhancing systemic visibility. Increased connectivity is transforming what is visible, that is, how the behaviors of individuals, groups, and technological devices can be observed and perceived (Leonardi & Treem, 2020). This means that organizations will have more profound knowledge about their business environments, customers, and other relevant stakeholders (Davenport, 2014). Leonardi and Treem (2020) assert that in a connected environment, not only the collected data but also the absence of data will become a form of digital data, and thus "there is no opt-out; there is no way to be invisible" (p. 1603).

Data represent the surrounding environment in a form that can be observed and analyzed. Therefore, data enable the visibility of systemic entities, their relationships, and past and predicted performance. Leonardi and Treem (2020) argue that behavioral visibility, which they define as "the socio-material performance of the behavior of people, collectives, technological devices, or nature in a format that third parties can observe through minimal effort such that patterns, causes, or motives can be inferred" (p. 1605), is one of the most fundamental changes associated with organizing in the age of datafication.

The ever-increasing incorporation of the Internet into all aspects of life has led to most service integration taking place in digital platforms that track data. For instance, it has been predicted that by 2025, 95 percent of service interactions will be handled via computerized technologies (Morgan, 2018). The interactions are traceable, and many feed real-time data into the databases used to gain service ecosystem visibility.

The increased connectivity raises visibility expectations (Leonardi & Treem, 2020). The more data an organization collects, the greater the expectation that it will have information about its environment and make that knowledge visible to other actors, including those who contributed to data collection. The ecosystem literature acknowledges that actors' expectations drive the evolution of service ecosystems as actors adapt to one another based on their expectations of change (Gulati, 1998). According to S-D logic, these changes in behavior over time shape norms and culture—that is, institutions that govern interactions in the service ecosystem (Vargo & Lusch, 2016). Therefore, it can be assumed that increased data utilization and enhanced interaction visibility increase systemic visibility.

With systemic visibility, we imply that actors and other entities of the service ecosystem, as well as their relationships, become more visible (i.e., transparent). In line with Leonardi and Treem (2020), we anticipate that increased systemic visibility will affect how actors and ecosystems function and organize. This is assumed to happen on and across individual (micro), organizational (meso), and societal (macro) levels.

As argued by Davenport (2014), big data influences not only technology and management processes, but also the methods and culture of working. As data processes, tools, and applications spread and evolve, they will inevitably transform our perspectives on decision making, management practices, formulating competitive strategy, and value creation (Pappas et al., 2018).

Enhanced visibility and its indirect effects, such as privacy concerns, can already be observed in data regulation, although institutions related to data use are still in their infancy (Pappas et al., 2018). Some of the first initiatives have been put into practice, such as the European Union's General Data Protection Regulation (GDPR) and MyData, a data governance initiative that emerged from open data activism and aimed to assist individuals and organizations in gaining human-centric value from personal data. These regulatory initiatives gained traction, especially after the Cambridge Analytica scandal, in which Facebook user data were acquired and used to target ads for the November 2016 US election. These recent regulatory developments have altered how individuals and organizations view the use of personal data and have created new roles and

responsibilities for organizations (Flyverbom et al., 2019). These changes at the institutional level have increased the complexity of contemporary data-rich service ecosystems, which should not be ignored in the service ecosystem literature.

3.1.3. Data as a resource driving innovation. There is a widespread expectation that creating vast quantities of diverse data presents a tremendous opportunity for organizations to advance their products and services. In particular, data-driven decision making can be advantageous for firms' innovation processes, which often involve significant uncertainty and risk (Niebel et al., 2019). Innovation is often considered a top priority in service research and practice (Bitner et al., 2015; Ostrom et al., 2015). This is mainly because service innovation allows organizations to increase their productivity, profitability, and competitive advantage, among other advantages.

Innovation involves the creation of new products, services, and systems, as well as new demands and markets (Luo, 2022). The innovation process is characterized by creativity and novelty, and there is always uncertainty, posing a challenge to the actors aspiring to innovate. However, the enhanced ability to utilize data in the innovation process is anticipated to inform and inspire innovators and businesses to innovate (Luo, 2022).

Historically, innovation processes have relied primarily on human intelligence. However, rapid advancements in data available through connected devices, data computation, and AI capabilities will enable the accumulation of knowledge and enhance innovation, thereby making innovation processes more data-driven and AI-empowered (Luo, 2022). For instance, data can improve the discovery of new business opportunities through data mining or help conceptualize those with design generation using algorithms.

Data resources can be classified as shareable assets (Mamonov & Triantoro, 2018). They contribute to knowledge exchange and learning and can be applied to creating new products, services, and processes (Davenport, 2014). Data can interact with complementary resources, such as additional datasets and analytics, to become a source of value that other actors in the service ecosystem could not capture on their own (Mamonov & Triantoro, 2018).

Data are also assumed to benefit the innovation process in cases when actors in a service ecosystem hold different opinions, beliefs, values, or norms regarding how to seek solutions and approach situations as problems (Chandler et al., 2019). Due to the amplified opportunities to identify, retrieve, and exploit data and the increased knowledge about the potential uses of data in innovation processes, we anticipate that individuals working in service development and innovation will transition toward becoming more data-driven. Figure 1 summarizes our understanding of the functional roles of data (i.e., connecting actors, enhancing visibility, and driving innovation) in service ecosystems. The prevailing institutions (e.g., values, norms, and regulations) guide these processes and the overall use of data.

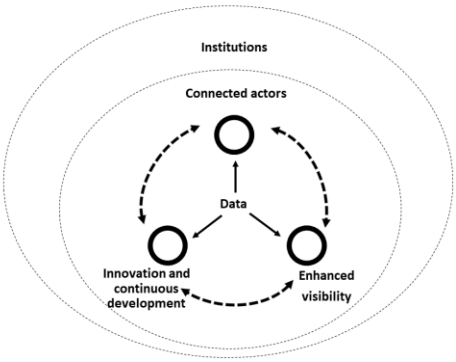

Figure 1. Functional roles of data in service ecosystems

3.2. The role of data at multiple levels of aggregation

In the context of data, an ecosystem typically refers to a community of interacting individuals and organizations that both influence and are influenced by the data (Curry, 2016). These data ecosystems have become more intertwined with service ecosystems, and the purpose of this paper is to enhance our understanding of how these two ecosystem approaches interact and enable value creation.

We understand data ecosystems as "socio-technical complex networks in which actors interact and collaborate to find, archive, publish, consume, or reuse data as well as to foster innovation, create value, and support new businesses" (Oliveira et al., 2019, p. 589). Multiple factors contribute to the emergence of such data ecosystems, including the evolution of digital technologies and political/institutional initiatives such as the open data movement (Oliveira et al., 2019).

A data ecosystem is comparable to a service ecosystem. However, Oliveira et al. (2019) suggested that data ecosystems differ from service ecosystems in that they do not necessarily have a shared platform for collaboration; instead, the common "platform" consists of collections of data exchanged by actors.

In the data ecosystem literature, the process by which data contribute to value creation is referred to as the data value chain, emphasizing the key activities that characterize data-based value creation (Curry, 2016; Lim et al., 2018). The value chain approach considers

data value creation to include activities such as data acquisition, analysis, curation, storage, and utilization (Curry, 2016). This does not imply that the process is always conducted by a single actor but that there is often a single actor driving the process.

Each actor in a data ecosystem performs one or more roles and is connected to other actors through relationships based on shared interests (Oliveira et al., 2019). Actors can play multiple roles (e.g., data suppliers, technology providers, and regulators) and collaborate across multiple systemic levels and contexts (Curry, 2016).

In their literature review, Oliveira et al. (2019) identified three contexts that can motivate or constrain the functioning of data ecosystem components. The first is the regulatory context, which includes laws, policies, standards, and agreements. Its primary function is to direct the structure and interrelationships of ecosystem components. The second is the institutional context, which refers to the values, rules, and norms that drive and constrain the behavior of ecosystem actors. The third is the technological context, which consists of technologies and operators facilitating connections between ecosystem entities. According to S-D logic, these enablers and constraints pertain to the institutions that govern interactions within the service ecosystem.

S-D logic (Vargo & Lusch, 2004, 2008, 2016) emphasizes the importance of institutions in comprehending the structure and operation of service ecosystems. Institutions are comprised of rules, norms, and beliefs that enable and constrain the intentions and actions of actors. For analytical purposes, these institutions and their assemblages can be viewed at the micro, meso, and macro levels of aggregation. At the micro level, the focus is on individual and dyadic structures and activities; at the meso level, the focus is on midrange structures and activities; and at the macro level, the emphasis is on broader societal structures and activities (Akaka et al., 2014; Vargo & Lusch, 2008).

Next, we discuss the relationships between the components of data ecosystems (e.g., Curry, 2016; Oliveira et al., 2019) and their embeddedness in various aggregation levels of service ecosystems (Figure 2).

3.2.1 Micro-context: Individual/dyadic actors leveraging the value of data. According to S-D logic, the prerequisites for service exchange are the creation, integration, and application of resources by actors in collaboration with other actors (Vargo & Lusch, 2014). At a micro level, actors provide, collect, process, use, and share data (Lim et al., 2018) to leverage their value by identifying new opportunities, enhancing decision making, enhancing products and services, reducing costs, and optimizing operations at an individual and/or dyadic interaction level (Davenport, 2014; Huhtala, 2022; Lavalle et al., 2011; Saarijärvi et al., 2014).

3.2.2. Meso-context: Midrange networks of actors facilitating the use of data for value creation. At the meso level, actors integrate their resources to create value and influence other actors directly and indirectly (Chandler & Vargo, 2011). In this context, actors facilitate the use of data in midrange structures and value creation activities by providing a context for developing connections, technologies, and strategies. For instance, organizations can invest in developing shared data infrastructures that allow other parties to participate in data-related activities.

3.2.3. Macro-context: Complex ecosystems of actors enabling and constraining the use of data in value creation. According to S-D logic, resource integration at the macro level occurs in complex networks within broader societal structures and activities. These networks consists of actors with the same interests, but often different ways of working and varying objectives. Actors at the macro level enable and constrain the use of data by encouraging, developing, regulating, and standardizing the use of data in service exchange.

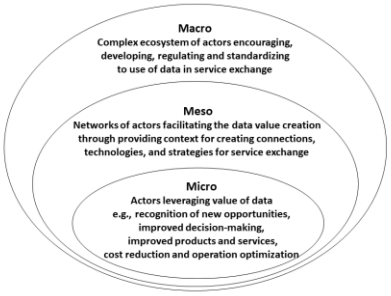

Figure 2. The embeddedness of the data ecosystem within the micro, meso, and macro levels of service ecosystems

4. Discussion: Rethinking the role of data in service ecosystems

This paper seeks to extend the understanding of the role of data in service ecosystems and thus contribute to the ongoing discussion of actors' resource integration and value co-creation efforts, and the role of institutions in guiding these processes in such ecosystems and at various levels of aggregation (micro, meso, and macro). We explore the role of data in service ecosystems from both functional and structural perspectives and provide novel insights into the emerging phenomena of (big) data and how it transforms service ecosystems across industries.

The literature reveals that the role of data in service ecosystems has increased due to the growing number of connected devices and machines, the widespread application of sensors, and the unprecedented increase in online content. Almost every action can be digitally traced and tracked, and the data can be refined and used in continuous service development and innovation. Hence, data play an increasingly critical role in value creation, and data ecosystems are becoming more intertwined with service ecosystems at all levels of aggregation.

At the same time, actors aim to preserve an appropriate level of privacy in ecosystems and stay ahead of competition. Given these opportunities and tensions, there is a pressing need to scrutinize the role and properties of data in service ecosystems. Vargo and Lusch (2016) have called for scholars to contribute to developing the S-D logic approach to make it a more holistic, dynamic, and realistic perspective of value creation in contemporary service ecosystems. Acknowledging that data plays an increasingly important role in service ecosystems and that service ecosystems are increasingly intertwined with data ecosystems, we argue that knowledge from both fields should be synthesized to advance the current S-D logic discourse. Therefore, based on the discussion in this paper, we suggest the following proposals to complement the extant literature:

***Proposition 1*. Data as a resource connect actors and shapes institutions in service ecosystems.** The literature views data as a shared resource, and its creation and use involve multiple actors at different stages of the data value chain (Curry, 2016). Empirical findings support the data's role in connecting actors for value co-creation (Xie et al., 2016). This is in line with S-D logic, which posits that resources connect actors and are thus valuable (Chandler & Vargo, 2011). Alaimo et al. (2020) argue that in the digitalized world, all business relationships and connections are based on data and can be conceptualized as "data relations." The increased availability and use of data transforms interactions (Xie et al., 2016), and changes in interactions become apparent on a larger scale in changing institutions.

***Proposition 2*. Data as a resource enhances systemic visibility and drives innovation**. The increased connectivity and subsequent increase in data are transforming what can be seen. The behaviors of individuals and the functioning of devices and machines can be observed and analyzed in more detail and more extensively than ever before. We argue that this enhances systemic visibility—that is, that actors and other entities of the service ecosystem, as well as their relationships, become more visible (i.e., transparent). Enhanced systemic visibility will enable the accumulation of knowledge and enhance innovation, thereby making innovation processes more data-driven (Luo, 2022).

***Proposition 3.* Data have become a dynamic meta-resource that is embedded in all levels of aggregation in service ecosystems.** Data flow, vary, and expand continuously, like the world it represents; therefore, data should be viewed as a dynamic resource. Data connect actors, enable visibility and shared understanding, and drive the use of other resources and innovation. Therefore, we propose conceptualizing it as a dynamic meta-resource, as suggested by Levitin and Redman (1998). With this, we mean that every service ecosystem and interaction within it is based on data of some kind. This means that the data ecosystem is present and functions beyond every aggregation level of the service ecosystem. As we show in Figure 2, the focus on the micro level is on individual and dyadic structures and activities; at the meso level, the focus is on midrange structures and activities; and at the macro level, the emphasis is on broader societal structures and activities.

By conceptualizing data as a meta-resource, we contribute to the literature focusing on resources enabling value creation (e.g., Akaka et al., 2014; Akaka & Chandler, 2011; Constantin & Lusch, 1994; Vargo & Lusch, 2004), which is currently based on two main types of resources: operand and operant. Based on the exploration in this paper, we argue that data is more than an operand resource, but it may not have the capability to act as such, as defined by S-D logic (e.g., Constantin & Lusch, 1994; Vargo & Lusch, 2004). Therefore, in this paper, we argue that the role of data as a dynamic resource should be viewed not only as an operand resource but as a meta-resource that acts beyond the traditional conceptualizations. According to S-D logic, resources attract actors and enable the exchange of services. Hence, viewing data as a dynamic resource may provide novel insights into actors forming partnerships and joining or disjoining networks.

By conceptualizing data as a meta-resource, we also see it contributing to the recent discussion on metahuman systems (Lyytinen et al., 2021) as new, emergent socio-technical systems where humans and machines learn jointly. The integrative resource in this collaborative process is data, enabling machines and humans to develop their capabilities. Viewing data as a resource in this process provides novel and intriguing paths for further research.

The proposals above aim to contribute to the S-D logic and service ecosystems literature and inspire further research. In the contemporary, connected, and fast-changing world, none of its systemic parts can be seen in isolation. Therefore, we see that future research should take a holistic view and focus on the institutional

changes and tensions that relate to the use of data in service ecosystems, as we expect these will play an increasingly important role in value co-creation and how innovations emerge in the future.

5. Conclusion

Data are expected to become an increasingly valuable resource for service organizations. Companies are estimated to increase their investment in data ecosystems and related processes (Capgemini Research, 2021). This means that organizations will transform their processes and develop their capabilities to realize the full potential of newly available data resources, which will, in the longer term, impact institutions. We argue that a significant opportunity can be found in studying data as a dynamic meta-resource in service ecosystems, and the topic needs further conceptual work, empirical research, and exploration.

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