Data & Knowledge Engineering 150 (2024) 102280

Contents lists available at ScienceDirect

Data & Knowledge Engineering

journal homepage: www.elsevier.com/locate/datak

Issues in inter-organizational data sharing: Findings from practice and research challenges

Ilka Jussen [a,*], Frederik Möller [b,c], Julia Schweihoff [a,b], Anna Gieß [b,c], Giulia Giussani [d], Boris Otto [a,c]

[a] TU Dortmund University, Joseph-von-Fraunhofer-Straße 2-4, Dortmund, Germany
[b] TU Braunschweig, Mühlenpfordstraße 23, Braunschweig, Germany
[c] Fraunhofer ISST, Emil-Figge-Straße 91, Dortmund, Germany
[d] International Data Spaces Association, Emil-Figge-Straße 80, Dortmund, Germany

ARTICLE INFO

Keywords:
Data sharing
Qualitative Interview study
Data ecosystems
Actor-network theory

ABSTRACT

Sharing data is highly potent in assisting companies in internal optimization and designing new products and services. While the benefits seem obvious, sharing data is accompanied by a spectrum of concerns ranging from fears of sharing something of value, unawareness of what will happen to the data, or simply a lack of understanding of the short- and mid-term benefits. The article analyzes data sharing in inter-organizational relationships by examining 13 cases in a qualitative interview study and through public data analysis. Given the importance of inter-organizational data sharing as indicated by large research initiatives such as Gaia-X and Catena-X, we explore issues arising in this process and formulate research challenges. We use the theoretical lens of Actor-Network Theory to analyze our data and entangle its constructs with concepts in data sharing.

1. Introduction

Data are a versatile digital good for companies to optimize internally, enrich existing products and services, derive new knowledge, or sell them [1–5]. They are a highly potent vehicle to optimize processes in inter-organizational business ecosystems, such as in complex *Original Equipment Manufacturer (OEM)* and *supplier* relationships in automotive supply chains [6]. While data are often compared to physical resources, they have key characteristics that clearly distinguish them. For example, given that data and the resulting digital products and services are reproducible at almost zero marginal costs, they have various underlying implications for how they can be used economically, e.g., in markets [7–9]. Extending the value and logic of using data as a resource internally is *data sharing*, which opens up new areas of value creation and improvements for organizations [10]. Quintessentially, data sharing is making data available to third parties for various purposes (e.g., value creation or optimization) through transferring (meta-)data or granting access to data for algorithm training [11,12]. As a result, companies do not have to empty their repertoire of customer data. Instead, they can benefit from supplementing it with data from other companies, fostering new sources for inter-organizational cooperation and competition [13]. Nevertheless, companies are reluctant to share data, given many concerns and barriers associated with the process [14,15]. Reluctancy to share data is not something new and was already observed by Hirschheim and Newman [16] in a case study revealing an array of concerns by data providers. The juxtaposition of these incentives and barriers leads to various tensions in data

* Corresponding author.
E-mail address: ilka.jussen@tu-dortmund.de (I. Jussen).

https://doi.org/10.1016/j.datak.2024.102280
Received 17 February 2023; Received in revised form 11 December 2023; Accepted 7 January 2024
Available online 10 January 2024
0169-023X/

sharing, such as finding an adequate data value without knowing the objective worth of data [17]. Enders et al. [18] examined decision criteria for companies to share data, such as the dangers to competitiveness, data misappropriation, the potential for innovation, and legal and privacy aspects. Opriel et al. [19] studied problems in data sharing explicitly for automotive supply chains, entailing, for instance, the unknown benefits for others, lack of data quality, misuse of data, or trust. The issue of data quality in itself is paramount for any data-driven activity. Especially once data is shared, data quality must be "fit for sharing" when transferring data to others [20 p. 3]. From a business perspective, companies fail to see the immediate benefit of data sharing in a B2B environment and entangle the process with a plethora of concerns, such as ensuring data governance, privacy, or legal agreements [21,22].

Today, the issue of data sharing is more pressing than ever since modern digital technologies (e.g., sensors) constantly produce data about real-world processes. A study by the European Commission [23] shows that 80 % of industrially generated data is unused. In that regard, a study by PWC [24] found that companies primarily share data with customers, followed by suppliers and others outside the company. The same study shows that large and small, and medium-sized enterprises (SMEs) predict the growing relevance of inter-organizational data sharing in the coming years. The importance of inter-organizational data within the European Union has become increasingly present in recent years, as shown by the development of various legal standards. In addition to the General Data Protection Regulation Act (GDPR), the Data Governance Act (DGA) and the Data Act (DA) complement the legal framework for data sharing. These new legal frameworks are expected to generate additional growth of the gross domestic product within the European Union of up to € 270 billion by 2028 [23,25].

Given the above, we find that data sharing is a complex socio-technical issue (e.g., Jussen et al. [26]) that is riddled with an array of relevant decisions organizations have to consider. For example, one of the most fundamental questions is: *What data do I share with whom under which conditions?* Against the backdrop of large-scale European research projects (e.g., [27,28]) and the exponentially increasing amount of data in organizations (e.g., Parvinen et al. [5]), we identify a significant push in politics and industry to tackle the issue of sovereign data sharing. Correspondingly, we observe a rising interest in research investigating various elements of data sharing, such as the uncovering of barriers to data sharing [15], reporting on specific data sharing use cases (e.g., Stein et al. [29]), business models (e.g., Schweihoff et al. [30]), the organization of data ecosystems [31] or the emergence of research tracks (e.g., Möller et al. [32]). Our primary motivation for this explorative study is to complement these research activities, uncover issues arising during inter-organizational data sharing, and formulate research challenges for this novel field. This results from a lack of deep analysis of real-world data-sharing use cases that reflect the modern trajectory of using data to foster value co-creation (see studies above). To address this, we pursue the following research question: *What are the issues in inter-organizational data sharing?* We performed a qualitative interview study with 14 informants reporting on (public and private) data-sharing initiatives in Europe. We enriched these interviews by analyzing public data on an additional 28 data-sharing cases. To analyze the data, we followed established guidelines for transcription and data analysis across cases [33,34]. When necessary to reaffirm our understanding, we invited each expert for a second round of discussion, reflecting on our analysis of each case and presenting our produced results. We opted to conduct an interview study because, in the literature, data sharing issues are still emerging, with some papers reporting on empirical and conceptual findings (e.g., van den Broek and van Veenstra [35]). Various data-sharing organizations are still young, allowing us to study emerging concepts. These insights can be captured through interviews with experts [36], working on industry-driven projects, and research consortia. We do not extract these findings in a vacuum but use Actor-Network Theory (ANT) as a *theory for explaining* and *theory for analyzing* [37]. ANT is suitable for this purpose since it helps to explain how networks, such as data-sharing ecosystems, come together, how the motivations of actors pay into these complex relationships, and how these networks stay together and create superordinate benefits (e.g., Callon [38], Walsham[39]).

The paper is structured as follows. After the introduction, we outline the fundamentals of data sharing in general and in the context of ANT. Then, we detail our research approach consisting of a qualitative interview study and public data analysis. Next, we present our findings as data-sharing issues across the data-sharing process. Ultimately, we formulate research challenges, discuss limitations, and close with an outlook about further research.

Table 1
Selected definitions of data sharing.

Selected definitions	Source
"The term 'data sharing' is used in order to describe all possible forms and models underpinning B2B data access or transfer."	European Commission ([42] p. 5)
"Data sharing is a label that may cover different economic modalities: sharing for free, trading for a monetary compensation or in exchange for other data, direct sharing of a dataset or indirect sharing of a data-based service only."	European Commission ([47] p. 14)
"Data sharing is the domain-independent process of giving third parties access to the data sets of others [...] The shared data is often used to develop new applications and services. The expectation is to be compensated financially or through other benefits (e.g., receiving data) for providing the data. What the data may be used for and how it is made available is determined within the framework of the (legal) agreements between the data providers, data consumers, and other roles, depending on the use case."	Jussen et al. ([26] p. 3688)
"Data sharing can allow organizations to access complementary data sources and help them develop innovative applications and services. We considered data sharing as either third parties' opening the data they own or their consuming the data from other providers."	Vesselkov et al. ([11] p. 303)

2. Background

2.1. Data sharing

Quintessentially, the purpose of inter-organizational data sharing is the reciprocal generation of organizational benefits in the minimal bilateral relationship between a *data provider* and a *data consumer* [26,40,41]. In that regard, sharing data can be both an intrinsic activity that has an ultimate purpose or can be incentivized through receiving something in exchange, such as monetary compensation, other data, or services [14,40]. Table 1 lists selected definitions of data sharing, illustrating that it is not 'just' about a technological process but a set of activities that touches a variety of business decisions (e.g., economic interests or governance) [26]. Principally, *sharing data* grants others the right to access or transmit data in a minimum bilateral business relationship [42]. Other definitions include sharing derivatives of data, such as services based on data, which are shared instead of the actual raw data [43]. Parties involved in data sharing usually include a keystone actor that shares data and data consumers that receive them, e.g., customers, suppliers, or business partners [20,44,45]. It is the permitted release of data used by other individuals, regardless of the application context [46]. Since data sharing necessarily means giving something away, there is a significant need to establish legal frameworks between involved actors to define data sharing and its operationalization [26]. What these definitions show is the basic understanding of data sharing, granting organizations access to external data that they can not access on their own for an array of purposes, such as developing new services [11].

Data sharing cumulates in data ecosystems that are demarcated data-sharing networks, resulting in the emergence, design, and economic exploitation of new opportunities, such as services and products. They are "a set of networks composed by autonomous actors that directly or indirectly consume, produce or provide data and other related resources" [41 p. 4] and need to be established to "unlock the potential benefits of data sharing" [48 p. 590]. Subsequently, data ecosystems can be seen as a product that emerges through frequent data sharing between actors that take on different roles, such as data producers, data consumers, and intermediaries [41]. Data sharing exists in horizontal and vertical collaboration with other actors and can even involve forms of coopetition [45,49]. Taking these views reveals the complexity of data sharing since it is entangled with many concepts detailing specific aspects. For instance, large research projects (e.g., Gaia-X) and a distinct stream of research investigate *data sovereignty* [50]. *Data sovereignty* clarifies sovereignty rules for actors in a data ecosystem sharing data by defining usage control policies, rights, and regulations for data utilization [49]. It regulates the "self-determination of individuals and organizations with regard to the use of their data" [50 p. 550].

2.2. Actor-network theory to conceptualize data sharing

ANT is an established and widely used theory to investigate phenomena at the intersection of the social and technology in IS research [51]. In this socio-technical sphere, it aims to analyze the emergence of networks of human and non-human actors based on their motivations [39]. In inter-organizational data sharing, organizations build data ecosystems to solve problems or generate new opportunities [48]. As a result, ANT has the potential to be a suitable vehicle for understanding this socio-technical relationship in-depth since its core logic reflects how data-sharing relationships emerge. Over time, different constructs have been proposed in ANT, of which we focus in particular on the *translation process*, i.e., the emergence of the networks (e.g., see Walsham [39], Sarker et al. [52], or Uden [53]). In the past, ANT has already been used to make sense of ecosystems. For example, Chen and Hung [54] used it to analyze innovation ecosystems, and Kaur and Ahmed [55] drew on ANT to study Information and Communication Technology for Develop-

Table 2
Definitions of concepts in ANT relevant to the study and their application to data sharing.

Concepts	Definition	Application to Data Sharing
Problematization	"first moment of translation, during which a focal actor frames the problem in its own term, identifies other relevant actors, and highlights how the problem affects the other actors" ([52] p. 54)	Identifying motivations (e.g., create new business models,) problems-to-be-solved by data sharing from multiple parties, such as: **Data Provider:** Identify a problem that requires data sharing to be solved (to sell/share data). **Data Consumer:** Identify a problem that requires data sharing to be solved (to buy/receive data).
Intéressement	"intéressement, involves convincing other heterogeneous actors that the interests defined by a focal actor for them a in fact, consistent with what their own interests should be." ([52] p. 55)	Getting another party on board and motivating them to share data (i.e., through incentives or shared problems) for the common good, for example, through establishing incentive mechanisms and defining issues relevant to solving the problem in *Problematization*.
Enrolment	"Enrolment is when another actor accepts the interests defined by the primary actor. This is the third moment. It is how to define and coordinate the role." ([53] p. 87)	Define, accept, and align roles amongst data sharing parties. Negotiate terms of data sharing between parties (i.e., usage control policies) and operationalize the data sharing process based on Intéressement.
Mobilization	"Maintaining the network by persuading the actants that their interests are the same as the translator" ([56] p. 6)	Establishing continuous data sharing between parties through extending existing data sharing or growing the data ecosystem.

ment (ICT4D) ecosystems.

ANT has two dominant units of analysis: *actors* and *networks*. *Actors* are all human and non-human entities that shape their environment by acting in it, creating dependencies, and explicating dedicated will [57]. Actor networks consist of actors with aligned interests, including "people, organizations and standards" [39 p. 468]. In the case of inter-organizational data sharing, we define actors as organizations in different roles that share data and actor networks as the resulting data ecosystems consisting of at least two organizations that share data to generate value for all parties. Depending on the specifics of the data ecosystem, these parties can be expressed through different roles. For example, Oliveira et al. [48] provide a meta-study on roles in data ecosystems, finding a broad spectrum including, e.g., *data providers, data brokers*, or *data curators*. In a bilateral data-sharing case in the automotive industries, Zrenner et al. [6] only refer to two roles in *data providers* and *data consumers*. Reporting on the case of International Data Spaces (IDS), Otto and Jarke [49] give examples of the roles of *data providers, data users*, or *software providers*.

We explicitly draw from *translation*, which is how actors align to act in a network and generate value co-creatively (see Table 2). The process comprises four sub-processes: *problematization, intéressement, enrolment*, and *mobilization* [53,58]. *Problematization* is the "first moment of translation, during which a focal actor frames the problem in its own term, identifies other relevant actors, and highlights how the problem affects the other actors" [52 p. 54]. Transferred to data sharing, we see problematization as the original activity of a focal actor to identify a problem that can be solved using data and potential partners that can either provide these data or want to consume them. Next, *intéressement* requires convincing other actors that engaging in solving the initial problem offers reciprocal value for all parties involved [52]. In the case of data sharing, we see that process as the negotiation of terms under which data sharing is supposed to take place. Third, *enrolment* defines and enacts roles and their alignment regarding shared values in achieving a common goal [39,53]. In data sharing, we view *enrolment* as the definition and acceptance of roles, the agreement on operationalizing data sharing, and the conceptualization of the corresponding regulatory mechanisms imposed by that infrastructure. Lastly, *mobilization* refers to the crystallization of a stable core of a network that ensures continuous data sharing [39,53,59].

3. Method

Since our study is explorative in nature, the first task was to identify a strategy for contacting potential experts who could report on inter-organizational data sharing [60]. We had the chance to use an E-Mail distributor of an umbrella organization facilitating data spaces and thus address a wide circle of experts dealing with data sharing in various capacities and roles. Data spaces are one technical realization of data sharing, enabling providers and consumers to share data on a shared 'playing field' with a predefined set of rules and standards [49]. Subsequently, tapping into these data spaces is highly likely to yield informants engaging in data-sharing issues regularly that possess performative or epistemic expertise in data sharing [61]. Complementary to this, we had sponsors who provided us access to informants (i.e., a 'known sponsor' approach, Patton [62]).

In total, we had access to 14 informants reporting on 13 data-sharing cases (some cases overlapped). In one interview, there were two interviewees. After the first round of interviews, nine informants were interviewed again to ask for feedback, discuss the findings, and answer existing questions. We triangulated our conclusions using a secondary data source and expanded the initial interview study through the qualitative analysis of 28 data-sharing use cases based on publicly available data (see Table 6 in the appendix). As a result, we constructed a database of data-sharing organizations and coded the public information (e.g., websites, blog posts, or other documents) based on the findings from the interview study. The primary purpose was to validate the interview findings and identify blind spots in our initial results (see Table 3). To ensure that public data can be used in a meaningful way, we have focused on data-sharing organizations that provide enough information in the English or German language (e.g., Remane et al. [63]), have a distinct focus on data sharing (e.g., as a data space, Jarke et al. [50], Weking et al. [64]), and that was still active at the point of us conducting the study. This strategy is sensible because we found data-sharing organizations to be very transparent (similar to business models, Teece [65]) in sharing the underlying logic of their inner workings (e.g., who shares data with whom). Subsequently, using reliable public sources, such as websites or news articles, is potent to reaffirm our study and identify relevant issues (e.g., Hartmann et al. [2]). Fig. 1 visualizes the qualitative study design.

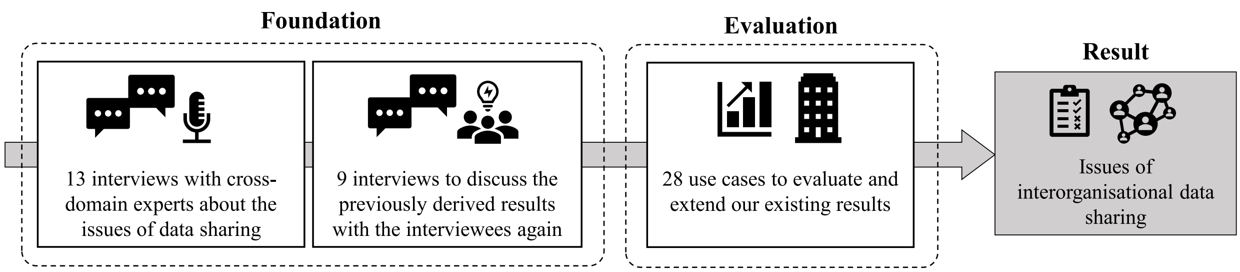

Fig. 1. Illustration of the qualitative research design.

Table 3
Overview of the interview study.

#	Cases	Duration Interview [min]	Duration Evaluation [min]
1	1	38:54	~20-30 Minutes
2	2	38:24	
3	1	52:13	
4	1	46:46	
5	1	52:02	
6	1	1:06:10	
7	1	54:44	
8	1	44:33	
9	2	51:31	
10	1	54:04	-
11	1	45:08	-
12	1	35:41	Written Feedback via E-Mail
13	1	35:16	-

3.1. *Data collection*

We designed an interview guide based on the translation mechanisms in ANT to generate comparability in the semi-structured interviews. Semi-structured interviews have the advantage of giving the interviewer a 'checklist' to ask pivotal questions while leaving the interviewee enough freedom to report on their valuable experiences and leaving the interviewer room for improvisation if necessary [36,62]. The study generated over 10 h of interview material and approximately 3 h of evaluations (see Table 3). The interviews were all conducted online. The length of the interviews varied in some cases, which can be attributed to the technical background of the interviewees and how they answered, for example, by explaining more than one data-sharing case. All interviews were conducted in German or English and recorded, fully transcribed, and coded. This ensured that we counteract the volatility of the spoken word and the roughness of *ad hoc* note-taking, as well as deeply familiarize ourselves with our data [66,67].

During each interview, at least two authors were present to ask questions, ensuring that all questions would be asked, and no vital information would be missed. After the interviews, there was a brief discussion between the interviewers to capture the initial findings. If available, we complemented findings from the interview study with publicly available data from the websites of the organizations. The pivotal advantage of collecting data on multiple cases against single case studies is the cumulative analysis of a unit of analysis across a series of cases [68].

That allows for extracting data across cases and enables comparative analysis, which is highly beneficial for the validity and generalization of the results [69]. In our case, we explicitly profit from analyzing these multiple cases for data sharing as "[t]he theory is emergent in the sense that it is situated in and developed by recognizing patterns of relationships among constructs within and across cases and their underlying logical arguments" [70 p. 25].

3.2. *Data analysis*

Before we entered the systematic coding procedure, we asked the informants, if necessary, for a second meeting to clarify open questions and evaluate our understanding of the underlying case. For this purpose, we constructed a visual representation of how we understood the data-sharing scenario and an overview of the most relevant issues based on the predefined interview guide in a PowerPoint presentation. Out of the initial sample of 13 interviews, we evaluated our findings with 9 of them in subsequent meetings and received written feedback from another one (see Table 3). Each session took between 20 and 30 min, and each participant was given a chance to comment on the validity and accuracy of our findings and suggest room for improvement. Of course, we also used these appointments to fill in information gaps where necessary. To perform the coding process, we followed the recommendations of Gioia and Corley [34] (see Fig. 2). In the first step, we open-coded all interviews line by line and generated low-level codes (1st order concepts) that were very close to the actual statements of the informants [71]. In the next step, we performed aggregative axial coding to find relationships between individual codes through screening for similarities to reduce the set of 1st-order concepts logically to 2nd-order themes. For instance, we generated low-level codes referring to issues of data monetization and business models, which we aggregated to higher-level concepts, such as *data for monetary compensation* or *data for data*. In the third step, we created aggregated dimensions to substantiate our coded data structure. Referring to the former example, all codes that reference some kind of counter value for data have been grouped under the dimension of *remuneration* (see Fig. 4). In the next step, we used ANT as a *theory for explaining* and *theory for analyzing* [37] to make sense of and structure the data structure based on the translation process outlined above (see Section 2 and Table 2). This process can be described as systematic mapping, in which we explicitly looked for findings from our interviews and how to map them to the constructs of the translation process in ANT. We found this procedure to be highly sensible since ANT is a well-proven theory to explain how networks come together while considering the motivations of each actor. On the other hand, it gave us distinct pointers on what to look for and how to analyze the final coding structure.

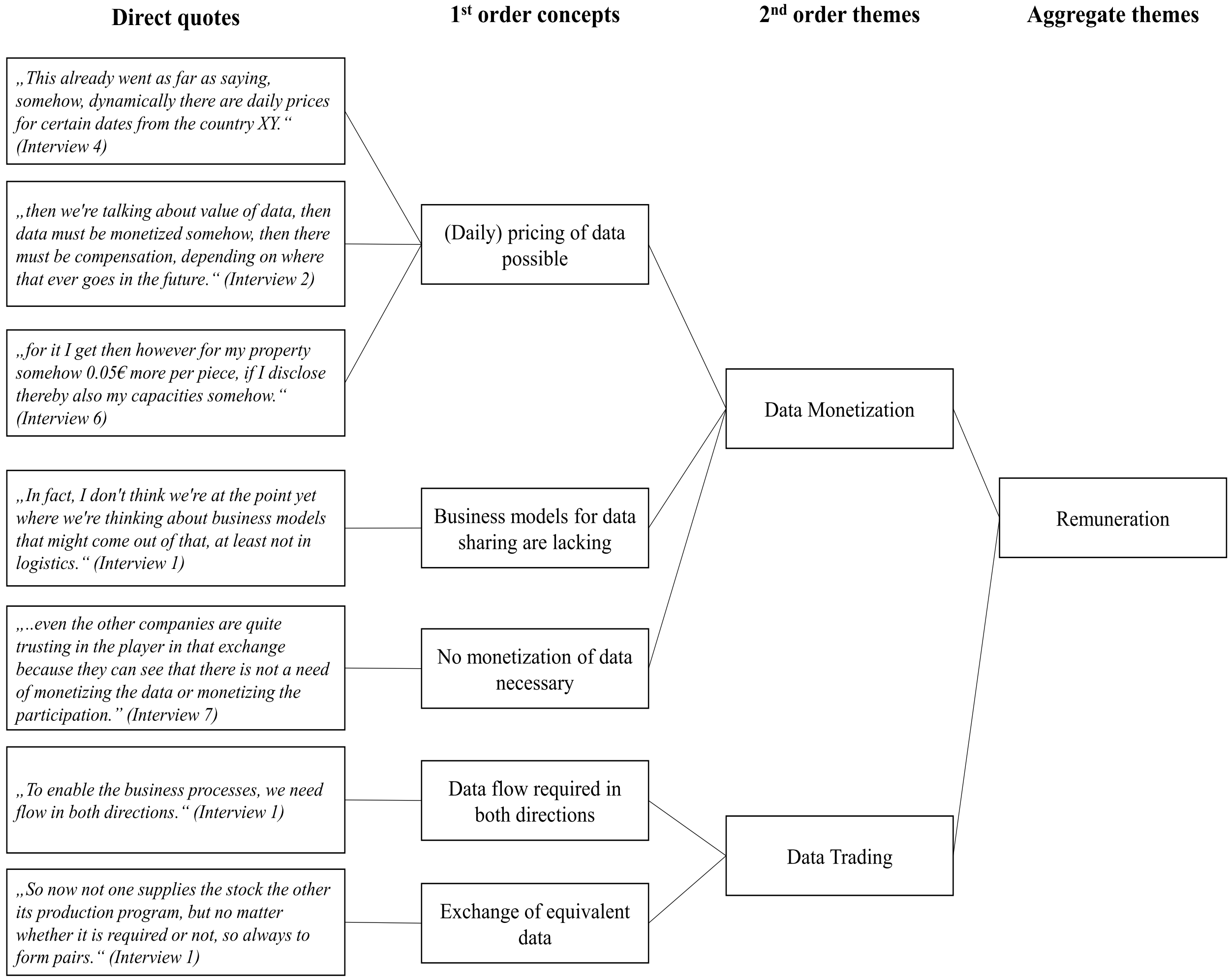

Fig. 2. An illustrative example of the Gioia diagram.

4. Findings: issues in inter-organizational data sharing

Our research brought to light an array of key issues and decisions organizations face in the inter-organizational data-sharing process (see Fig. 3). Drawing from ANT, we organized the individual steps in the frame of the translation process (see Table 2) in *problematization, intéressement, enrolment*, and *mobilization*. While ANT has a rich repertoire of constructs to offer that would merit additional studies (e.g., betrayal), it is the process of translation that we are interested in for the study.

In **problematization (phase I)**, initiating factors influence data-sharing motivation. In this phase, we find prerequisites for data sharing, which, mandatorily, are required. We also worked out two driving factors from two logics of data sharing. **First (1)**, organizations share data to solve some particular problem, for instance, to acquire an improved service. **Second (2)**, organizations explore the availability of new business opportunities. In **intéressement (phase II)**, the motivation is translated to generating a data-sharing ecosystem, which is suitable to solve the problems defined earlier or realize incentives. These ecosystems vary depending on the underlying use case resulting in different required roles, the network structure (e.g., peer-to-peer data sharing or data sharing through an intermediary), or the *modus operandi* of participation (e.g., the existence of an entry fee). Naturally, these data-sharing ecosystems require rules that determine how data consumers can use data. This can happen either on an actor level in a bilateral agreement or, complementarily, based on rules set by the ecosystem providing a governance structure. A pivotal component in these negotiations is the remuneration a data provider receives for delivering data.

In **enrolment (phase III)**, data sharing is operationalized by building the appropriate infrastructure, which is the cumulation of technical realization, the implementation of security measures, and the explication of the data-sharing logic (e.g., peer-to-peer vs. marketplace). A typical example is the formation of bilateral data sharing (e.g., in supply chains) instead of larger-scale multilateral data-sharing organizations that require more complex technical infrastructure. During operationalization, the parties must define the scope of data sharing, ranging from only sharing data to integrating additional services (e.g., analytics, data quality). Naturally, this influences what components are relevant to data sharing. In **mobilization (phase IV)**, the data ecosystem aims for two goals. On the

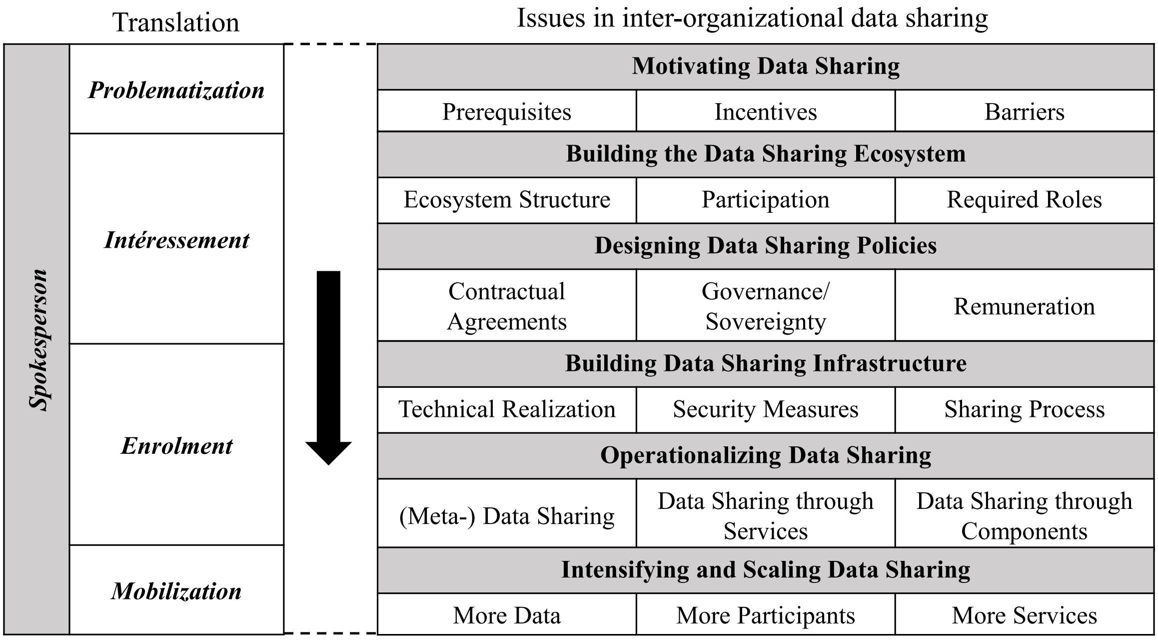

Fig. 3. Issues in inter-organizational data sharing mapped to the translation process in ANT.

one hand, to *intensify (1)* data sharing between data providers and data consumers (e.g., sharing more data in existing data provider and consumer relationships) as well as *scale (2)* them (i.e., growing the amount of data providers and consumers). In addition to the four phases of ANT, the use of a **translator**, a so-called spokesman, is explained in the literature. According to Callon et al. [72], a translator "speaks in the name of the constituents or the social classes he aims to represent." Generally, these **spokespersons** help to increase the acceptance of a solution and expand the emerging ecosystem [53].

4.1. Problematization: which problems does data sharing solve?

We found that those willing to share data often draw from two justifications, either with incentives relating to new business opportunities or problems they want to solve. To give these findings structure, we inductively categorize both the *problems to be solved* and the *incentives* for data sharing in the categories of *economic, technical*, and *social* (Fig. 4). In terms of overlap, we categorized them based

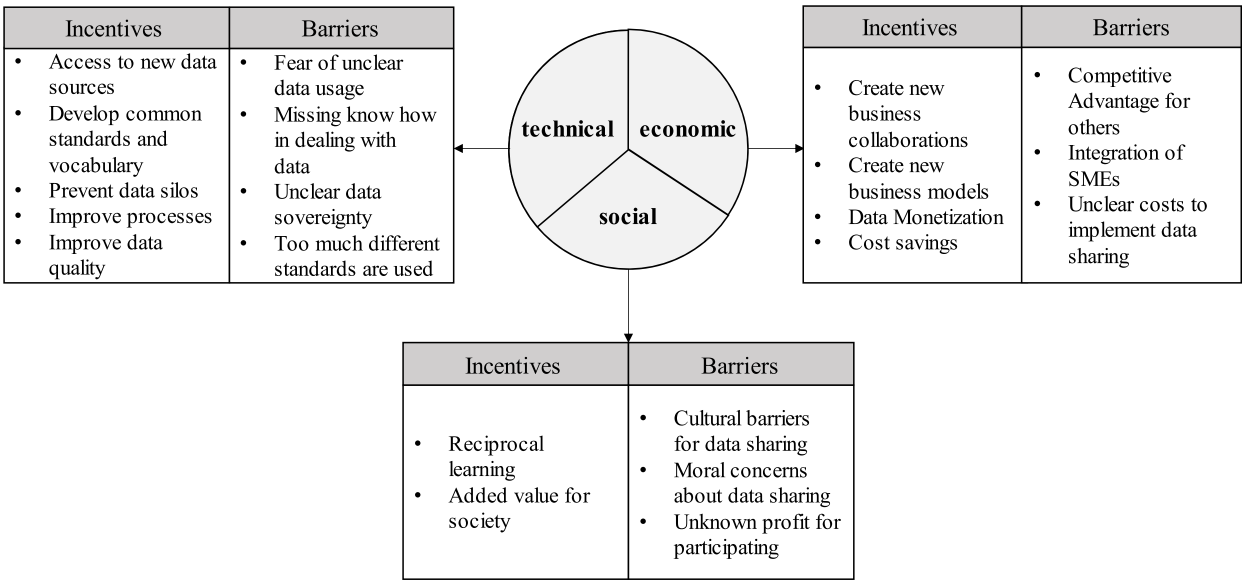

Fig. 4. Motivations in inter-organizational data sharing.

on the thematic focus and our judgment. Accordingly, the classification is an orientation but not a fixed assignment. **Economic** incentives, on the broadest level, usually refer to the generation of new business models, finding new business opportunities and business relationships, as well as monetizing data, and saving costs through data sharing.

From a **technical** perspective, this includes gaining access to new data sources and breaking down data silos. One example of a technical incentive is the joint development of vocabulary and standards to improve data quality and associated processes across company boundaries. In the **social** dimension, data sharing can help organizations in reciprocal learning and sharing experiences. In some cases, the goal was to create added value for society, in the words of one informant: *"It is generated for the public and the (…) society, if you will, and beyond (Interview 8)."*

Solving existing problems and overcoming barriers is the other side of the coin that motivates data sharing. Consider social factors such as cultural or moral barriers that prevent data sharing with companies from specific regions or the unclear added value of why data should be shared with others in the first place. Illustrative economic barriers are competitive advantages for other organizations or unclear implementation costs of data-sharing activities:

> *"You also potentially have SMEs in this sharing. So you have somehow small, I don't know, up to a craftsman's business for me, and on the other hand, (…) a global corporation, then, of course, the question arises (Interview 4)."*

The technical barriers include concerns about data use. For example, this consists of the technical realizability of data sovereignty policies or the ability of organizations to handle data appropriately. *"Then you need certain technical skills in-house, and that is not always there (Interview 8)."* Another issue is the landscape of existing data standards prevalent in different organizations, further complicating the data-sharing process.

In addition to the incentives and barriers, certain requirements must be met before organizations can share data. By prerequisite, we mean aspects that are mandatory and non-negotiable, although they can be strengthened by following processes, such as the development of contracts. Prerequisites include a fundamental willingness to share data with others and the creation of transparency and trust between stakeholders: *"Trust within a data market is a prerequisite for participants feeling safe to share also personal and proprietary data* [73].“

4.2. *Intéressement: what is needed to motivate and realize data sharing?*

In *Intéressement,* actors need to be convinced to engage in data sharing [52]. To answer how to realize data sharing, we have defined two core elements that need to be agreed upon with their sub-aspects. An essential part is ***building the data-sharing ecosystem*** (see Table 7 in the appendix), which covers *participation, required roles,* and *ecosystem structure*.

Participation specifies the entry point, a possible membership fee, and rules for participation. There are usually two ways to participate in data sharing ecosystems. On the one hand, organizations can contact a central authority that manages the ecosystem. On the other hand, if the ecosystem is managed by the community, participation in the community can be sufficient: *"That would again reduce the entry level for new participants, and that is what we are looking for. Make it easy (Interview 10)."* Currently, several cases we analyzed offer free *membership* but have plans for future monetization. Naturally, the traditional bilateral mode of data sharing is negotiated directly between one data provider and one data consumer. As *rules for participation* in data sharing, we identified several possibilities. For instance, some require users to undergo a validation process to increase trust on the ecosystem level:

> *"We have even an enrolment phase. So we can meet the player and then verify who is [the] player and who is taking part in the ecosystem even within the contract and so on. And then we have even validation test for the API, so before the publication of the API, we can yeah understand even the quality of the API. So that if the API does not reach the quality, it will not be in the catalog (Interview 7)."*

We found great variety in the ***required roles*** and categorized them into the superordinate roles of *provider, consumer,* and *intermediary* (similarly to Oliveira et al. [48]). Inter-organizational data sharing can manifest through a variety of providers. Apart from the apparent provision of data (data providers), there are also providers of additional services based on data (service providers). One example is offering digital twins as a service: *"The other case is that we have a digital twin of the material we produce or the products we produce. And offer that digital twin information to our customer (Interview 5)."*

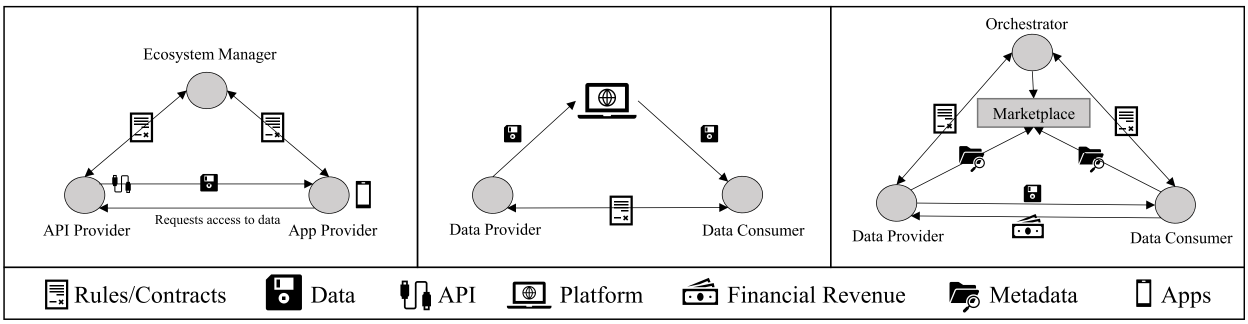

Fig. 5. Three examples of data-sharing ecosystems, their roles, and visualized structure.

Another set of roles is specific to an API-based data-sharing ecosystem, which comprises application, API, platform, and infrastructure providers (see Fig. 5). For a complete overview of roles, see Table 7 in the Appendix. Depending on the use case, intermediaries, such as *ecosystem managers, orchestrators, trusted third parties*, or *data trustees,* manage the data exchange process between providers and consumers but are not users of the data themselves:

> *"[s]o we have the three main roles; the participants, which can play one role, the other or both of them. We can have a participant who can only share data. We can have a participant who can only consume data, and we can have participants who do both activities and then we have the technical management board who manages the ecosystem (Interview 7)."*

Fig. 5 visualizes three approaches to data-sharing configurations. The center example shows data shared via a platform between data providers and data consumers who agree on contracts. The other two examples use different forms of intermediaries (e.g., *ecosystem manager* and *orchestrator*) that organize the exchange but are not directly involved in the process. In the example on the left-hand side, the app provider requests data from the API provider to develop apps with the data after accessing it. In the example on the right-hand side, the orchestrator has a contractual relationship with the participants and provides a platform for them. The providers and consumers make their metadata available on this platform. The data exchange and any possible remuneration occur directly between data providers and consumers, independently of the orchestrator.

The ***ecosystem structures*** are bilateral (1:1) or multilateral (n:m) and describe the relationship between data providers and consumers. In the typical bilateral supply chain setting, data is usually shared between producers and suppliers in a 1:1 relation, even though we find that informants strive to extend it: *"but we are currently restricting it to 1 to 1 (Interview 9)."* Multilateral data sharing occurs, for example, in complete domains (e.g., mobility) or cross-domains operationalized through central access points such as digital platforms (e.g., [74]). Established relationships often cement the traditional bilateral data-sharing relationship expressed through a lack of short-term motivation for extending data sharing or significant challenges in the technical realization: *"we come from the world of classic bilateral EDI communication. We connect each partner individually and exchange data with them (Interview 1)."*

The second element in the *intéressement* phase is ***designing a data sharing policy***, which includes *contractual agreements, governance/ sovereignty,* and *remuneration* (see Table 8 in the Appendix). Naturally, implementing ***contractual agreements*** includes a broad range of issues. The fundamental decision is whether sharing data requires new contracts or can be subsumed or integrated into existing contracts.

> *"Data governance policy that were not existing at (…). It was new then that policy written and validated by the management drive in our procedures, so we had to create that then we had all those all the passion on the data extraction and the enterprise architecture because most of our IT system when lying on the subcontractor and sometimes we were even not knowing what to do and how to extract data (Interview 3)."*

That depends primarily on whether the companies are already working together and whether contracts are already in place. BurstIQ's enterprise example seeks to use smart contracts to guarantee participants their data ownership [75]. However, this seems more of an isolated case, as smart contracts cannot fully replace traditional contracts. These *contractual agreements* must inevitably define data access, data control, or data usage policies. The contracts exist either between two participants directly (e.g., providers and consumers) or between the participants and a central authority, for example, the ecosystem manager.

Access to the data may be enabled in different ways. There is no obligation to share data; actors can opt only to consume data from others. The data provider can offer available data on-demand or via a data catalog. *Data usage policies* between all stakeholders specify how data may be used, how they are stored, and whether data export is possible. These usage policies can be technically enforced by using different technologies, such as *connectors* or APIs. Connectors are technical components prevalent in data space scenarios. They are essential for integrating data providers and consumers and as a solution for communicating usage policies and the data transfer itself. For instance, in some settings, connectors can be used to pass usage policies across multiple tiers in supply chains:

> *"Of course, there is no getting around the fact that we ultimately have to make the inheritance of usage policies possible […] It must, of course, be possible for the supplier on the third level to give the participant on the second level certain conditions of use; for example, that he may still be able to pass on the data to the first level but not to the OEM. So the connector of company 3 has to communicate with the connector of company 2 (Interview 6)."*

Similarly, APIs can also pass policies between actors that describe precisely how to use them and the data they provide: *"APIs even define, for example, the policy on how to use them, and these APIs are validated (Interview 7)"*.

Data control is essential to guarantee that data providers retain the decision with whom to share data under which conditions (e.g., for how long). This could result in the data provider necessarily remaining the data owner: *"They decide with whom to share data, but there is not by default shared to anybody, of course. There [are] strict rules and mechanisms to ensure that the data sharing is down only on the few data assets they want to share (Interview 3)."* Even if the data enters the system of other companies, it still belongs to the data provider. Other companies only receive permission to use these data for a specific purpose. Accordingly, the data provider can retain the right to withdraw consent to use the data and potentially end the data-sharing process:

> *"As long as the customer gives us his data for these, let's say, bilateral analyses,* i.e., *before the sharing, before the consent, this is the customer's data. That is, if the client says they are ending a contract with us and they want to take all the American data out of it, then they can do that (Interview 4)."*

Moreover, we identified ***governance and sovereignty*** issues as important areas before organizations can share data. Data sovereignty policies can be part of the existing contractual framework. These contracts guarantee that data sovereignty remains with the data provider:

> *"Another associated benefit is data sovereignty: Your data remains on-site, you retain full control and can decide for yourself whether and for what purpose your data is sent to external systems or supply chain partners [76]."*

Furthermore, sovereignty must be implemented technically. For example, this includes the platform or APIs requiring additional authentication: *"So we have a sort of a legal framework in addressing the data sovereignty, not specifically a technical way. The technical way is in APIs with the authentication (Interview 7)."* Data providers can accept or reject access to their data or APIs and define usage policies. The cases differ because some propose a minimum governance framework on an ecosystem level that can be a product of collaboration based on personal responsibility or be mandatorily set by the ecosystem orchestrator. In one case, the informant reported on an elected board having responsibility for the governance structure of the ecosystem.

> *"Regarding the governance, so we have great industries, which is one of these sector organizations, and then we have a supervisor report with which is an elected board every two years we will elect 2 participants per stakeholder group (Interview 11)."*

When organizations are willing to share their data with others, they expect to get remuneration. We have identified three ways for ***remuneration*. First (1)**, the exchange data for data of equal perceived value. **Second (2)** data exchanged for services or access to an improved service based on shared data. **Third (3)**, the last and currently most difficult variant is data exchanged for money. The latter option is intuitive, yet we found little evidence that this mode of remuneration is viable at this point in time. One informant reported on the principle of *quid pro quo*, which mitigates issues of data monetization through sharing data of perceived equal value, leading to the perceived fairness of the transaction.

> *"Whether it is then, in the end, the popular quid pro quo principle so ultimately that one behaves reciprocally so that one, if one gets data, at the same time or gives data, rather, that one in return also gets back data that contain a comparable value (…), but it can of course also be that one can possibly also monetize data sets that one gives away and accordingly then gets back another equivalent value (Interview 2)."*

Similarly, Databroker suggests ways for providers to price data. In addition to the free offer, they propose both fixed prices for data and flexible pricing through market-driven or on-demand pricing [77]. Fig. 6 shows four examples of remuneration for data sharing. Data donation stems from HEALTH-X DataLOFT. In one of its use cases, they describe the possibility of stakeholders voluntarily donating their data for research purposes without expecting a direct service in return. Data providers are always assured of having control over their data [78]. Furthermore, the data consumer may pay the data provider for providing data. We see this, for example, in the case of Advaneo, which gives a price to data sets in its marketplace [79].

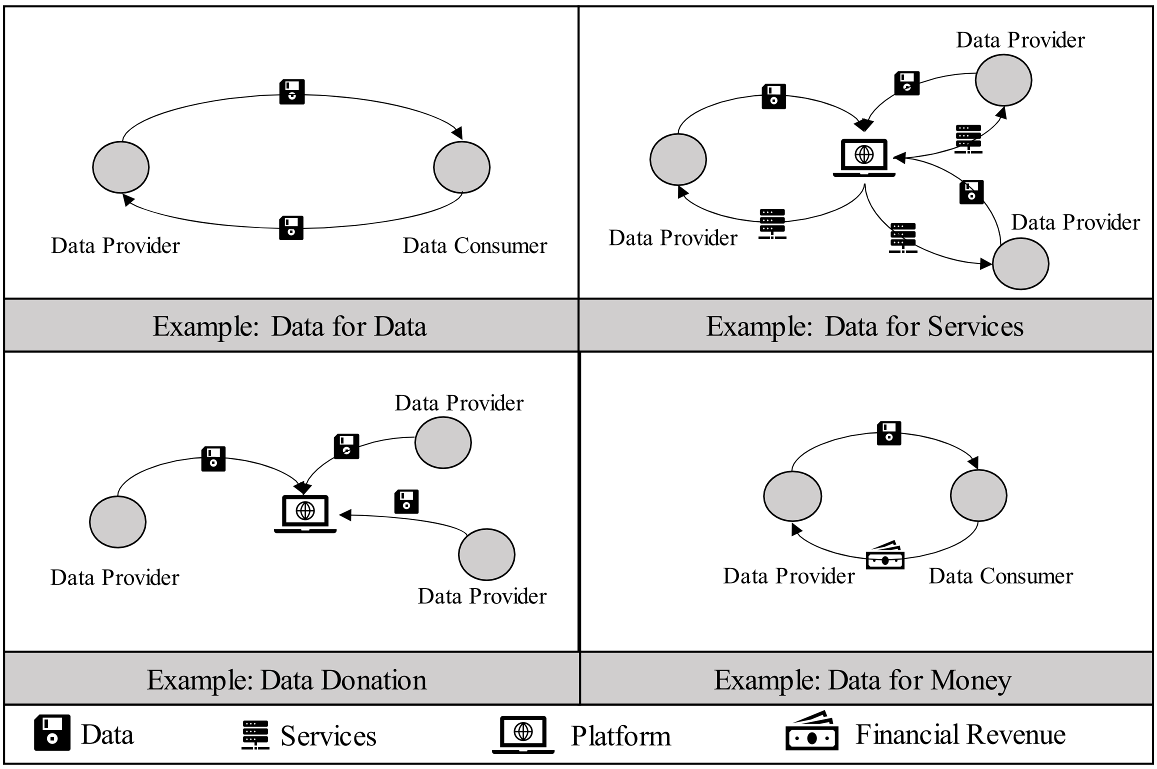

Fig. 6. Four examples of data sharing remuneration.

4.3. Enrolment: how to operationalize data sharing?

The next phase of *enrolment* is ***building data-sharing infrastructure*** and how to ***operationalize data sharing*** with *technical realization, security measures,* or even the *sharing process* itself (see Table 9 in the appendix). In ***technical realization***, we use the terms platforms, data spaces, or marketplaces. These terms are often used synonymously in the interview without defining them. Sometimes use cases offer an additional app store for a platform that provides extra services related to data sharing. The use of connectors is suggested for connecting the actors to the platform: *"Custom connector software acts as an adapter – between data sources, multiple parties, or the various components [80]."* However, actors may develop their connectors and certify them by independent organizations: *"you can even use your own connector, but you need to get it certified (…), so that's rather simple (Interview 10)."* While in the past, data sharing used standards such as EDI (Electronic Data Interchange), today, it is mainly APIs. These APIs serve as gateways to gain access to specific data sets. Technical standards help simplify data sharing: *"we need a standard way of data sharing (Interview 9)."*

Data formats and data quality standards should be firmly defined between the participants. But using cross-sectoral standards such as the IDS, IDSA, or Gaia-X standards is also helpful. Furthermore, ***security measures*** should be implemented to ensure data security and data quality. *Data security* is ensured through certification processes, tokens, keys, or encryption. In this way, it is possible to increase the trust of the stakeholders in the data sharing processes: *"we need to demonstrate that our technology is secure cyber-protected entering data confidentially ensuring that the data integrity will (Interview 3)."*

Ensuring data quality is a major challenge for many companies regarding data sharing, as it is also associated with costs: *"So it's always this trade-off, how much do I have to invest in order to create how much quality (Interview 4)."* In the interviews, we learned that data quality is critical between companies and within the individual companies themselves and is constantly under review. We captured four strategies for data quality management. **First (1)**, a certain level of data quality is defined between data providers and consumers within a network. Keeping the data quality level is a prerequisite for participation in data sharing: *"So you shouldn't have to discuss the quality of data. It has to be a fixed level of quality. Corresponding requirements must be fulfilled. That must be the case in any case (Interview 2)."* **Second (2)**, another possibility is to use an app that serves as a neutral control authority to check the quality of the data (e.g., the data format). **Third (3)** is a multi-step process where data providers and consumers must register to become part of the ecosystem. The actors need to decide which data they will share and who is the owner of the data to build trust. Then there is validation and testing using APIs to determine how the data is shared. **Fourth (4)**, the ecosystem sets basic rules (e.g., use of a specific XML schema), extended by further requirements of the concrete application area.

In the ***sharing process***, it is essential to consider how the actual data exchange takes place and which technologies, if any, are used. One possibility is the direct exchange of data. Additionally, data sharing can occur through digital platforms (e.g., marketplaces) or within data spaces. Depending on the underlying technology, either data or metadata are shared directly or through an intermediating agent. In the case of data spaces, usually, the participants share meta-data and only share data directly and bilaterally once the data provider and the data consumer accept predefined conditions for data sharing:

> *"That is one of the key assets that the data flow does not go via the data space but between the connectors only […] so the metadata is stored centrally in the broker (Interview 10)."*

Fig. 7 shows two options for data-sharing infrastructure. Technical data exchange usually occurs via a platform or data providers and consumers directly. In data exchange over a platform, standards are defined between providers and consumers. The data is uploaded to a platform via connectors. The consumer, linked to the platform via connectors, can access the data. It is possible to expand

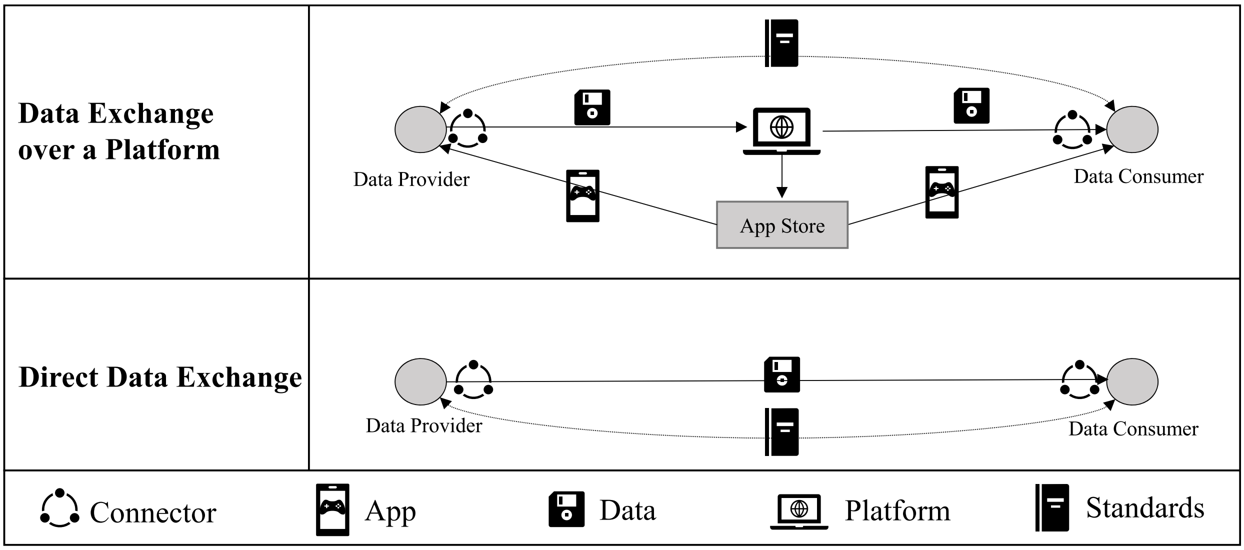

Fig. 7. Two examples of data sharing infrastructure.

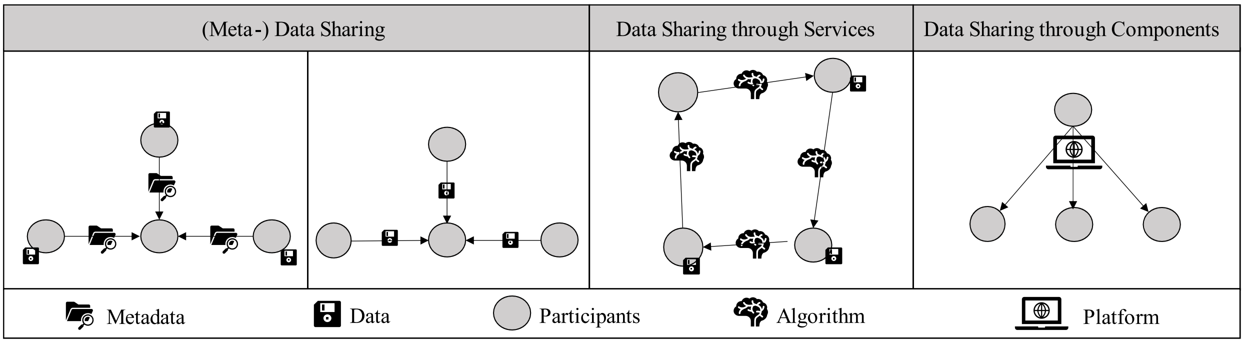

Fig. 8. Four examples of data sharing operationalization.

the platform with an app store, which the actors can access. In direct data exchange, the players are connected via connectors and have defined standards beforehand. Here the possibility of encrypting data is shown to guarantee data security and to grant access to the data exclusively to authorized consumers: *"At the end of the day, we use, [company] is also very strict about this, keys for certain networks that you can only manage at [company] (Interview 4)."*

Technologies such as cloud applications, artificial intelligence, blockchain, or machine learning enable data sharing: Examples like Databroker [77] use the blockchain to implement data-sharing marketplaces. They use blockchain technology to secure data exchange since the DataBorker platform does not gain access to the data and cannot manipulate it. In this case, the blockchain enables transparent and efficient transactions between the data user and the data provider. As a possible use for machine learning in data sharing, one interview partner considered the creation of time series analyses. Based on the data, it would be possible to make predictions for the future that are as accurate as possible: *"This is precisely the idea that is then also being pursued with blockchain solutions (Interview 6)."*

Generally, technologies in data sharing are not only used for the implementation of data sharing itself but also for the hosting of existing services using new technologies like cloud applications: *"And we are currently working on, let's say, hosting more and more services in this cloud as well (Interview 4)."* The feedback from the interviewees shows that these technologies are currently sufficiently well-known but are still little used and will play a more important role in the future. One informant reported on a case in the health sector utilizing the shared use of an AI algorithm. Since the data is highly critical and personal, the stakeholders would not share the data but share an AI algorithm that would train on the data and then be made usable by others. Accessing and sharing the algorithm as opposed to the data itself mitigates data protection challenges (see Fig. 8).

After the basic framework conditions for data sharing have been defined, the next step is **operationalizing data sharing** (see Table 4). We find three possibilities to initialize data sharing (see Fig. 8). The most basic variant is (meta) data sharing. Naturally, the data types shared between organizations depend on the underlying use case and the domain in which they operate. Subsequently, these data types reflect a wide range, such as production data, master data, or process data. The type of **shared data** depends on the use case. Concrete data that is exchanged is, for example, machine utilization or production capacities, which are shared between producers and suppliers: *"[…] capacities in terms of production capacities (Interview 7)."*

Otonomo [81] illustrates the versatility of shared data, even from just one domain such as automotive (e.g., traffic data, weather data, parking data). Furthermore, there is the possibility that actors (e.g., service providers) offer ***services based on data sharing*** themselves to participate in the ecosystem. This covers a broad spectrum from simple matchmaking of participants to data quality as a service or access to a data sharing-based algorithm: *"they get access to an algorithm (Interview 8)."* The variety of services shows the possibilities that data sharing brings for pure data providers and service providers. But also, the provision of ***components*** or infra-

Table 4
Three ways to operationalize data sharing.

Operationalizing Data Sharing		
(Meta-) Data Sharing	Data Sharing through Services	Data Sharing through Components
Metadata	Data Quality as a Service (e.g., updating the data, risk assessment)	Components for Data Sharing (e.g., sensors)
Production data (e.g., Machine utilization, Production capacities)	Matchmaking of participants (Catalogue with APIs…)	Reference architectures
Public data	Data Analysis for the Customer	Standard data models
Open data	Collaborative data management	Standard interfaces
Master data	Training for data handling	Software building blocks
Product data	Offer a digital twin	Offer infrastructure for data sharing (e.g., cloud platform as a service)
Process data (e.g., transport data)	Access to data-sharing-based algorithms	
	Consulting services	

structure is helpful to get the data-sharing process started. Many possibilities can advance the data-sharing ecosystem from data models to interfaces or entire architectures: *"we provide the components. We do not provide data (Interview 12)."*

4.4. Mobilization: how is data sharing implemented and established?

The final phase of ANT, *mobilization,* focuses on maintaining the ecosystem and the interests of the individual actors (see Table 10 in the appendix). Applied to our approach, this means ***intensifying and scaling data sharing*** (see Fig. 9). Intensify data sharing means gradually sharing more data to increase the added value for the participants in the future: "*from sharing as less as possible, [to] more and more, to as much data as allowed (Interview 5)*." However, more data should be shared, and the shared data should be used for multiple purposes. In this way, further standards and more elaborated use cases can be created.

Another goal for the future orientation is the scaling of data-sharing ecosystems with a more extensive number of actors. Multilateral data sharing will be introduced as a new standard, and data sharing between different data spaces or ecosystems is also aimed for: *"integration of all kinds of other data spaces in Europe and in the end to end up with some kind of Federated network of data spaces (Interview 11)."*

For example, one long-term goal of data spaces is to provide organizations with access to data in a specific domain and generate federated data spaces that enable data sharing through connected data spaces without domain or technology limitations. Furthermore, the explicit goal of these data-sharing ecosystems is to offer more services based on data sharing:

> *"Our vision: to pave the way for innovative data-driven services and for applications around machine learning or artificial intelligence [82]."*

Thus, more individualized services for the customers are the goal, requiring new business models to deal with shared services or services offered by intermediaries: *"There are some possibilities, but most of them may have an intermediary in the middle (Interview 9)."* These intermediaries offer different services, such as sovereignty services, to ensure compliance with policies and technology services dealing with the data infrastructure [83].

4.4.1. Spokesperson: who promotes the initiative?

Related to our research on inter-organizational data sharing, we found spokespersons to be either well-known personality who promotes the initiative, even customers of the initiative who consciously promote it positively, or associations that motivate its members to participate in data sharing. For example, the German Chancellor Olaf Scholz is promoting the data sharing initiative Mobility Data Space [84], as is the Minister of Economics and Climate Protection, Robert Habeck, who is promoting the Catena-X Automotive Network [28] initiative: *"Catena-X is the industrial policy lighthouse project for the digitalization of supply chains."* Other data-sharing initiatives, such as Corporate Data Quality (CDQ) [85] or Snowflake, promote their products on their websites with statements from their customers:

> *"Across all ecosystems, Snowflake enables millions of dollars in annual savings for Western Union by reducing engineering, maintenance, licensing, and support costs [86]."*

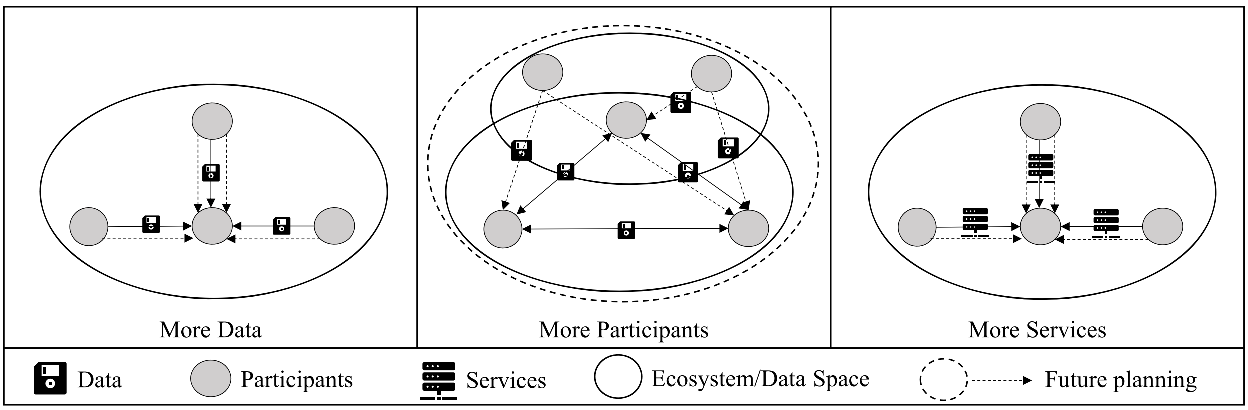

Fig. 9. Intensifying and scaling data sharing.

5. Reflecting on our findings: challenges for future research in data sharing and data ecosystems

Based on the findings we extracted from the interviews, public data analysis, and the relevancy of inter-organizational data sharing for practice and research, we formulate research challenges (see Table 5). Naturally, these challenges are not extensive, but we extracted a selection of challenges and questions during the study presented above through reflection.

First (1), we find multiple challenges relating to business models. Exploring the effect of data sharing and data ecosystems on business models is scarce (e.g., Schweihoff et al. [30]). For data ecosystems to flourish and grow, every participant needs to be able to sustain participation economically. Data sharing can, on the one hand, extend existing business models and, on the other hand, become the core of entirely new business models. For instance, some of the cases we analyzed received public funding to offset the data-sharing organization but are required to transition to economic independence once this funding runs out. Subsequently, finding sustainable business models in these settings is highly relevant for those organizing these data ecosystems. On the other hand, data providers and consumers will only participate in these data ecosystems if their business has some benefit. We also distinguish between new business models based on data sharing and integrating data sharing in existing business models, e.g., through enhancing or offering new services. Investigating the nature of how data sharing works in these business models could be a valuable way forward. Typical ways to analyze business models in IS research is building classification tools for data-sharing business models either focusing on a specific domain, technology, or a combination thereof [87].

Second (2), the emergence of multiple data-sharing organizations (e.g., multiple data spaces) potentially leads to new data silos. As a result, one key research field should be the federation of data ecosystems, which aims to bridge different data ecosystems and enable data sharing between domains. In general, the challenge is to mitigate how various data-sharing organizations interact with each other. Currently, we see that more and more data spaces arise for different industries or purposes (e.g., see [27]). Arranging the potential for collaboration between these data spaces in various domains (e.g., automotive and mobility) is key to ensuring maximum benefit for organizations and society. This possible way of bridging different fields relates to multiple dimensions, such as facilitating technical interfaces as well as finding business value.

> *"we talk all of Europe and globally with all kinds of databases popping up like mushrooms in nowadays and every domain in every country has its own data space and I think the challenge of the next years will be the primary focus will be on setting up this data space in the first place. But then the second question will be how to make sure that these Data Space can be Federated and can collaborate with each other (Interview 11)."*

Third (3), it remains unclear how organizations can be supported in making informed decisions when sharing data. The field of emerging decisions is extensive, ranging from data sovereignty issues (e.g., usage control or privacy) to data security and business models. A potential way forward is developing decision support. For example, business models usually rely on underlying configurations. Developing more tools explicitly tailored for data-sharing business models or specific instances of them (e.g., those using data spaces) has the potential to support researchers and practitioners. This also applies to other fields. It remains unclear what usage control policies need to be attributed to what type of data or how to identify the criticality of most data. It is assumed that this federation of data-sharing initiatives has a lot of potential, but the considerations on concrete implementation possibilities are still in the early stages. This will certainly be a challenge for future research.

Fourth (4), since data sharing and data ecosystems, in general, are emerging and large-scale projects and initiatives are relatively young, the long-term effects are unknown. Issues such as the effectiveness of business models (e.g., the ability to generate revenue) or usage control policies need to be observed long-term and analyzed in longitudinal studies. Especially the phase after initiating data sharing should be investigated, which could indicate the likelihood of permanent success through using or sharing new data as opposed to short-term motivation (e.g., as part of a publicly funded project). It should investigate whether patterns can be recognized and how

Table 5
Selected research challenges and research questions.

Research Challenges	Example research questions
Role-specific data-sharing business models	What are business models for specific roles in data ecosystems (e.g., data provider, data intermediary, or data consumer)?
	What are the business models for organizers of data-sharing ecosystems?
Federation of data sharing initiatives	What are the conditions for multiple data ecosystems to be interoperable and share data?
	How to ensure interoperability between different data-sharing initiatives (e.g., global data spaces or different domains)?
Decision support for inter-organizational data sharing	How to select suitable business models based on data sharing?
	How to select suitable technical infrastructure (e.g., data spaces) for data sharing?
	How to formulate data usage policies for specific application scenarios?
Longitudinal studies on inter-organizational data sharing	What are the long-term benefits of data-sharing business models and their critical success factors?
	What are the long-term effects of usage control policies and their effectiveness?
	What are the long-term benefits and risks of inter-organizational data sharing?
	What are typical patterns in modelling inter-organizational data sharing?
Technology use in data sharing	What are the advantages and disadvantages of using technologies in data sharing?
	What technologies can mitigate common barriers of data providers? (e.g., algorithm sharing)
	What is the impact of different technical realizations on data sharing? (e.g., data spaces or API ecosystems)

successful data-sharing architectures and concepts can look.

Fifth (5), using technologies emerges as a key issue for organizations relevant to data sharing. Some advantages include faster and more efficient data sharing, increased accuracy and reliability of data, and better decision-making. However, some disadvantages are also, such as security risks and privacy concerns. These advantages and disadvantages should be examined more closely. One example emerging from the interview study is sharing algorithms trained on data instead of sharing data. These alternative forms of generating shared data value, which might not require the actual transfer of data, could mitigate a range of barriers for data providers.

6. Contributions, limitations, and outlook

The **research community** is set to investigate the nature of data sharing more in-depth, e.g., as shown by the rising number of highly funded research projects, emerging research tracks, special issues, and published academic literature. Our study is one of the first to collect empirical data on how complex modern inter-organizational data-sharing organizations work. Using ANT, our study offers a unique view of uncovering data-sharing use cases and how they come together. In this, we shed light on problems solved through data sharing and motivations (e.g., incentives) for how actors engage in it. Since we provide a 'big picture' of data sharing issues, researchers can use our work to extend it with more issues or analyze specific issues more in-depth. For example, the complexity of supply chains can yield many more data-sharing issues spread over various relationships between suppliers, OEMs, service providers, or government agencies. Table 4 shows further research areas in the field of data sharing. Another exciting avenue for further research is to investigate data sharing under the lens of other theories, such as the resource-based view.

For **practitioners**, our study explores issues likely to influence their daily work soon. Against the background of large-scale industry initiatives (e.g., [28]), sharing data has significant potential to optimize entire industries. Our work syntheses relevant issues that practitioners can use as orientation when it comes to data sharing. Of course, our results are still more abstract, and the practical use requires more deep dives, but it offers a starting point to initiate this practice-oriented research.

Naturally, the study is subject to **limitations**. First, we provide insights for inter-organizational data sharing based on a qualitative interview study and public data analysis. This means that our interpretation might influence the results, which we tried to mitigate as best as possible (e.g., through discussion or reaffirmation with informants). Also, we could only talk to a subset of informants in inter-organizational data sharing, meaning extending the study by involving more informants might produce additional findings. Second, we applied ANT as a theoretical lens to give structure to our findings. However, this implies a process view that we do not expect every data-sharing initiative to follow. Instead, it is a means of giving structure that we found to be unstructured across the cases. Third, some of the issues we investigated would merit individual studies exploring them in-depth since they have a long tail of subsequent research questions. One particular example is *remuneration*. While we uncovered initial strategies (e.g., data vs. data or data vs. services), the issue of data monetization is complicated and needs to be explored in individual studies. In this respect, our study is limited to raising awareness of this and other issues and constructing a playing field for future studies to dig deeper. Ultimately, we had a rich database to generate findings. Yet, we learned that inter-organizational data sharing is highly individualized and depends on many variables (e.g., personal data or infrastructure), usually framed by specific cases. There are transferable settings (e.g., participation or required roles). However, the plethora of decisions and associated concepts is an issue too significant to tackle in one study. Some cases are similar, only differing slightly, while others differ significantly. For example, participating in data sharing can be subject to various conditions, such as paying a fee, using certain technologies, or agreeing to share data.

Various current studies show that sharing data is a central issue (see above). Subsequently, how data sharing works, what one must consider while doing it, and what implications it has for internal optimization and the co-creation of value is at the core of future decisions practitioners must make. Our issues are intuitively helpful and verified with practitioners to work as an orientation on setting up a data-sharing ecosystem. At the very least, these issues should be a checklist for practitioners to identify what they need to consider when they share data. The cases we have analyzed stem from various industries giving our results a broader character and higher transferability. Furthermore, data sharing is implemented with companies of the most diverse sizes, from smaller start-ups to SMEs to large OEMs.

CRediT authorship contribution statement

Ilka Jussen: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Validation, Visualization, Writing – original draft, Writing – review & editing. **Frederik Möller:** Conceptualization, Data curation, Methodology, Project administration, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Julia Schweihoff:** Conceptualization, Investigation, Visualization. **Anna Gieß:** Conceptualization, Investigation, Visualization. **Giulia Giussani:** Data curation, Project administration, Validation. **Boris Otto:** Funding acquisition, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

Acknowledgments

This research and development project is funded by the German Federal Ministry of Education and Research (BMBF) within the Incentives and Economics of Data Sharing Funding Action (IEDS004). The author is responsible for the content of this publication.

We also thank the reviewer team and the interview partners for their valuable time and input such as E015.

Appendix

Table 6, Table 7, Table 8, Table 9-10.

Table 6
Public data sharing cases.

No.	Use Case	Website
1	Advaneo	https://www.advaneo.de/#
2	Agdatahub	https://agdatahub.eu/en/
3	Agrigaia	https://www.agri-gaia.de/
4	AWS amazon	https://aws.amazon.com/de/?nc2=h_lg
5	burstIQ	https://burstiq.com/
6	Catena X	https://catena-x.net/de/
7	CDQ	https://www.cdq.com/
8	databroker	https://www.databroker.global/
9	Data Intelligence Hub	https://dih.telekom.net/
10	Dawex	https://www.dawex.com/de/
11	Dutch AI	https://nlaic.com/
12	Euhubs4data	https://euhubs4data.eu/
13	E015	https://www.e015.regione.lombardia.it/ https://www.cefriel.com/news-en/the-history-of-the-e015-digital-ecosystem/?lang=en(english)
14	Fiware	https://www.fiware.org/
15	German Edge Cloud	https://gec.io/
16	Health-X dataLOFT	https://www.health-x.org/plattform
17	INESECT	https://market40.eu/
18	Mobilitätsdatenmarktplatz	https://www.mdm-portal.de/
19	Mobilithek	https://mobilithek.info/
20	Mobility Data Space	https://mobility-dataspace.eu/de
21	Otonomo	https://otonomo.io/
22	Salesforce	https://www.salesforce.com/de/
23	SCSN	https://smart-connected.nl/de
24	Sensative	https://sensative.com/
25	Skywise	https://aircraft.airbus.com/en/services/enhance/skywise
26	Snowflake	https://www.snowflake.com/en/
27	TataSteel	https://www.tatasteeleurope.com/de/startseite
28	Trusts	https://www.trusts-data.eu/

Table 7
Building the data sharing ecosystem

Building the Data Sharing Ecosystem				
Participation	Entry Point	Contact central authority	Join the community	
	Membership Fee	Planned in the future	Free to participate	
	Rules for participation	Validation process for actors	Clear authentification	
Required Roles	Provider	Data Provider	API Provider	
		Platform Provider	APP Provider	
		Service Provider	Infrastructure Provider	
	Consumer	Data Consumer	End-user	Data User
	Intermediary	Ecosystem Manager	Trusted third party	
		Orchestrator	Data Trustee	
Ecosystem Structure	Structure	Bilateral	Multilateral (with a central access point)	
	Relationship	Producer-Supplier	Within a domain	Cross-domain

Table 8
Designing a data sharing policy

Designing a data sharing policy				
Contractual Agreement	Involved Actors	Between two participants	With the central authority	
	Data Sharing Contracts	Part of the existing contracts	Need for new contracts	
	Data Access	On-demand	Data catalog	No obligation to share data
	Data Usage Policies	Clear policies for data usage	Technical enabled with connectors	

(continued on next page)

Table 8 (*continued*)

Designing a data sharing policy			
		Define policies together	Implement access control
	Data Control	Data Provider remains the data owner	Provider decides with whom to share data and when
Governance/ Sovereignty	Legal Sovereignty	Data Sovereignty stays at the data provider	Data Sovereignty part of existing contracts
	Technical Sovereignty	over the platform	APIs with authentication
	Governance Framework	Decide within the ecosystem	Are already given between the actors
Remuneration	Data vs. Data	equivalent data	flow in both directions
	Data vs. Services	Better services/ components	
	Data vs. Money	Possible business models	Daily prices for the data
	Data Donation	Donate data for free	

Table 9
Building data sharing infrastructure

Building data sharing infrastructure					
Technical Realization	Technical Infrastructure	Platform	Portal	Apps / App Store	
		Data Space	Marketplace	Connectors	API
	Technical Standards	**Data Standards:**		**Existing Standards:**	
		Data Format (XML, JSON), Data Quality		IDS principles, IDSA standards, GAIA-X standards	
Security Measures	Data Security	Encryption	Tokens	Certification Process	
	Ensure Data Quality	Prescribed quality level for provider		The ongoing process for reviewing quality	
		App to ensure data quality		Rules to ensure quality	
Sharing Process	Exchange Process	Between the participants		Over the platform/ data space	
	Technologies	Cloud		Blockchain	
		Artificial Intelligence		Machine Learning	

Table 10
Intensifying and Scaling Data Sharing

Intensifying and Scaling Data Sharing More Data	More Participants	More Services
More data sharing to increase values for user Create standards for an entire domain Design more complex use cases Use of data for multiple purposes	• Develop sustainable and long-term data space • Enable data sharing between data spaces • Establish multilateral data sharing as standard	New individualized services for the customer Create business models for shared services and services provided by intermediaries

References

[1] H. Richter, P.R. Slowinski, The data sharing economy: on the emergence of new intermediaries, IIC - Int. Rev. Intell. Prop. Compet. Law 50 (2019) 4–29, https://doi.org/10.1007/s40319-018-00777-7.

[2] P.M. Hartmann, M. Zaki, N. Feldmann, A. Neely, Capturing value from big data—A taxonomy of data-driven business models used by start-up firms, Int. J. Oper. Prod. Manag. 36 (2016) 1382–1406, https://doi.org/10.1108/IJOPM-02-2014-0098.

[3] E. Alfaro, M. Bressan, F. Girardin, J. Murillo, I. Someh, B.H. Wixom, BBVA's data monetization journey, MIS Q. Exec. 18 (2019) 117–128, https://doi.org/10.17705/2msqe.00011.

[4] W. Günther, M. Rezazade Mehrizi, M. Huysman, F. Feldberg, Rushing for gold: tensions in creating and appropriating value from big data, in: Proceedings of the 38th International Conference on Information Systems, 2017.

[5] P. Parvinen, E. Pöyry, R. Gustafsson, M. Laitila, M. Rossi, Advancing data monetization and the creation of data-based business models, Commun. Assoc. Inf. Syst. 47 (2020) 25–49, https://doi.org/10.17705/1CAIS.04702.

[6] J. Zrenner, F. Möller, C. Jung, A. Eitel, B. Otto, Usage control architecture options for data sovereignty in business ecosystems, J. Enterp. Inf. Manag. 32 (2019) 477–495, https://doi.org/10.1108/JEIM-03-2018-0058.

[7] K. Pistor, Rule by data: the end of markets? Law Contemp. Probl. 83 (2020) 101–124.

[8] C. Shapiro, S. Carl, H.R. Varian, Information Rules: A Strategic Guide to the Network Economy, Harvard Business Press, Harvard Business School Press, 1998.

[9] D. Veit, E. Clemons, A. Benlian, P. Buxmann, T. Hess, D. Kundisch, J.M. Leimeister, P. Loos, M. Spann, Business models: an information systems research agenda, Bus. Inf. Syst. Eng. 6 (2014) 45–53, https://doi.org/10.1007/s12599-013-0308-y.

[10] J. Parra-Moyano, K. Schmedders, A. Pentland, Shared data: backbone of a new knowledge economy, in: A. Pentland, A. Lipton, T. Hardjono (Eds.), Building the New Economy, MIT Press, 2020.

[11] A. Vesselkov, H. Hämmäinen, J. Töyli, Design and governance of mHealth data sharing, Commun. Assoc. Inf. Syst. 45 (2019) 299–321, https://doi.org/10.17705/1CAIS.04518.

[12] R.W. Gregory, O. Henfridsson, E. Kaganer, H. Kyriakou, Data network effects: key conditions, shared data, and the data value duality, Acad. Manag. Rev. 47 (2022) 189–192, https://doi.org/10.5465/amr.2021.0111.

[13] B.R. Konsynski, F.W. McFarlan, Information partnerships—shared data, shared scale, Harv. Bus. Rev. 68 (1990) 114–120.

[14] J. Gelhaar, T. Guerpinar, M. Henke, B. Otto, Towards a taxonomy of incentive mechanisms for data sharing in data ecosystems, in: Proceedings of the 25th Pacific Asia Conference on Information Systems, 2021.

[15] M. Fassnacht, C. Benz, D. Heinz, J. Leimstoll, G. Satzger, Barriers to data sharing among private sector organizations, in: Proceedings of the 56th Hawaii International Conference on System Sciences, 2023.

[16] R. Hirschheim, M. Newman, Symbolism and information systems development: myth, metaphor and magic, Inf. Syst. Res. 2 (1991) 29–62.

[17] I. Jussen, J. Schweihoff, F. Möller, Tensions in inter-organizational data sharing: findings from literature and practice, in: 25th IEEE International Conference on Business Informatics, 2023, pp. 1–10.

[18] T. Enders, C. Wolff, G. Satzger, Knowing what to share: selective revealing in open data, in: Proceedings of the 28th European Conference on Information Systems, 2020.
[19] S. Opriel, F. Möller, U. Burkhardt, B. Otto, Requirements for usage control based exchange of sensitive data in automotive supply chains, in: Proceedings of the 54th Hawaii International Conference on System Sciences, 2021.
[20] S. Geisler, M.-E. Vidal, C. Cappiello, B.F. Lóscio, A. Gal, M. Jarke, M. Lenzerini, P. Missier, B. Otto, E. Paja, B. Pernici, J. Rehof, Knowledge-driven data ecosystems toward data transparency, J. Data Inf. Qual. 14 (2021) 1–12, https://doi.org/10.1145/3467022.
[21] R. D'Hauwers, N. Walravens, Do you trust me? Value and governance in data sharing business models, in: X.-S. Yang, S. Sherratt, N. Dey, A. Joshi (Eds.), Proceedings of Sixth International Congress on Information and Communication Technology, Springer Singapore, Singapore, 2022, pp. 217–225.
[22] J.B. Fisher, L. Fortmann, Governing the data commons: policy, practice, and the advancement of science, Inf. Manag. 47 (2010) 237–245, https://doi.org/10.1016/j.im.2010.04.001.
[23] European Commission, Data act: commission proposes measures for a fair and innovative data economy, 2022, https://ec.europa.eu/commission/presscorner/detail/en/ip_22_1113, accessed 18 March 2022.
[24] A. Pauer, L. Nagel, T. Fedkenhauser, Y. Fritzsche-Sterr, A. Resetko, Data exchange as a first step towards data economy, 2018, https://www.pwc.de/en/digitale-transformation/data-exchange-as-a-first-step-towards-data-economy.pdf.
[25] H. Mildebrath, Data Governance Act. BRIEFING EU Legislation in Progress, 2021, https://www.europarl.europa.eu/RegData/etudes/BRIE/2021/690674/EPRS_BRI(2021)690674_EN.pdf, accessed 19 March 2022.
[26] I. Jussen, J. Schweihoff, V. Dahms, F. Möller, B. Otto, Data sharing fundamentals: definition and characteristics, in: Proceedings of the 56th Hawaii International Conference on System Sciences, 2023.
[27] GAIA-X, Gaia-X Use Cases, 2021, https://www.gaia-x.eu/use-cases, accessed 23 November 2021.
[28] Catena-X Automotive Network, Catena-X, 2023, https://catena-x.net/en/, accessed 6 September 2023.
[29] H. Stein, C. Rix, A. Effertz, S. Bergau, W. Maass, Data sharing in the german food industry–empirical insights, in: Proceedings of the 28th Americas Conference on Information Systems, 2022.
[30] J. Schweihoff, I. Jussen, V. Dahms, F. Möller, B. Otto, How to share data online (fast)—A taxonomy of data sharing business models, in: Proceedings of the 56th Hawaii International Conference on System Sciences, 2023, pp. 607–616.
[31] D. Heinz, C. Benz, M.K. Fassnacht, G. Satzger, Past, present and future of data ecosystems research: a systematic literature review, in: Proceedings of the 29th Pacific Asia Conference on Information Systems, 2022.
[32] F. Möller, G. Strobel, T. Schoormann, B. Otto, Introduction to the minitrack on designing data ecosystems: value, impacts, and fundamentals, in: Proceedings of the 56th Hawaii International Conference on System Sciences, 2023.
[33] K.M. Eisenhardt, Building theories from case study research, Acad. Manag. Rev. 14 (1989) 532–550, https://doi.org/10.2307/258557.
[34] D.A. Gioia, K.G. Corley, A.L. Hamilton, Seeking qualitative rigor in inductive research, Organ. Res. Methods 16 (2013) 15–31, https://doi.org/10.1177/1094428112452151.
[35] T. van den Broek, A.F. van Veenstra, Modes of governance in inter-organizational data collaborations, in: Proceedings of the 23rd European Conference on Information Systems, 2015.
[36] M.D. Myers, M. Newman, The qualitative interview in IS research: examining the craft, Inf. Organ. 17 (2007) 2–26, https://doi.org/10.1016/j.infoandorg.2006.11.001.
[37] S. Gregor, The nature of theory in information systems, MIS Q. 30 (2006) 611–642.
[38] M. Callon, The sociology of an actor-network: the case of the electric vehicle, in: M. Callon, J. Law, A. Rip (Eds.), Mapping the Dynamics of Science and Technology: Sociology of Science in the Real World, Palgrave Macmillan UK, London, 1986, pp. 19–34.
[39] G. Walsham, Actor-network theory and IS research: current status and future prospects. Information Systems and Qualitative Research, Springer, 1997, pp. 466–480.
[40] C. Azkan, F. Möller, L. Meisel, B. Otto, Service-dominant logic perspective on data ecosystems: a case-study based morphology, in: Proceedings of the 28th European Conference on Information Systems, 2020.
[41] M.I.S. Oliveira, B.F. Lóscio, What is a data ecosystem?, in: Proceedings of the 19th Annual International Conference on Digital Government Research: Governance in the Data Age, 2018.
[42] European Commission, Towards a common European data space, 2018.
[43] B. Martens, A. de Streel, I. Graef, T. Tombal, N. Duch-Brown, Business-to-business data sharing: an economic and legal analysis. JRC Digital Economy Working Paper, European Commission, 2020.
[44] J. van den Hoven, Information resource management: stewards of data, Inf. Syst. Manag. 16 (1999) 88–90, https://doi.org/10.1201/1078/43187.16.1.19990101/31167.13.
[45] J. Gelhaar, B. Otto, Challenges in the emergence of data ecosystems, in: Proceedings of the 24th Pacific Asia Conference on Information Systems, 2020.
[46] I.V. Pasquetto, B.M. Randles, C.L. Borgman, On the reuse of scientific data, Data Sci. J. 16 (2017) 1–9, https://doi.org/10.5334/dsj-2017-008.
[47] European Commission, Business-to-Business data sharing: an economic and legal analysis, 2020, https://ec.europa.eu/jrc/sites/default/files/jrc121336.pdf, accessed 17 September 2021.
[48] M.I.S. Oliveira, G. de Fátima Barros Lima, B. Farias Lóscio, Investigations into data ecosystems: a systematic mapping study, Knowl. Inf. Syst. 61 (2019) 589–630, https://doi.org/10.1007/s10115-018-1323-6.
[49] B. Otto, M. Jarke, Designing a multi-sided data platform: findings from the International data spaces case, Electron. Mark. 29 (2019) 561–580, https://doi.org/10.1007/s12525-019-00362-x.
[50] M. Jarke, B. Otto, S. Ram, Data sovereignty and data space ecosystems, Bus. Inf. Syst. Eng. 61 (2019) 549–550, https://doi.org/10.1007/s12599-019-00614-2.
[51] O. Hanseth, M. Aanestad, M. Berg, Guest editors' introduction: actor-network theory and information systems. What's so special? Inf. Technol. People 17 (2004) 116–123.
[52] S. Sarker, S. Sarker, A. Sidorova, Understanding business process change failure: an actor-network perspective, J. Manag. Inf. Syst. 23 (2006) 51–86.
[53] L. Uden, Actor network theory and learning, in: N.M. Seel (Ed.), Encyclopedia of the Sciences of Learning, Springer US, Boston, MA, 2012, pp. 86–89.
[54] P.-C. Chen, S.-W. Hung, An actor-network perspective on evaluating the R&D linking efficiency of innovation ecosystems, Technol. Forecast. Soc. Change 112 (2016) 303–312, https://doi.org/10.1016/j.techfore.2016.09.016.
[55] R. Kaur, A. Ahmed, Unpacking actor interactions in ICT4D ecosystem, in: Proceedings of the 23rd Pacific Asia Conference on Information Systems, 2019.
[56] J. Rhodes, Using actor-network theory to trace an ICT (telecentre) implementation trajectory in an African women's micro-enterprise development organization, Inf. Technol. Int. Dev. 5 (2009) 1–20.
[57] M. Callon, B. Latour, Unscrewing the big Leviathan: how actors macro-structure reality and how sociologists help them to do so. Advances in Social Theory and Methodology, Routledge, Kegan Paul, Londres, 1981, pp. 277–303.
[58] M. Callon, Some elements of a sociology of translation: domestication of the scallops and the fishermen of St Brieuc Bay, Sociol. Rev. 32 (1986) 196–233, https://doi.org/10.1111/j.1467-954X.1984.tb00113.x.
[59] A. Cordella, M. Shaikh, Actor-network theory and after: what's new for IS research, in: Proceedings of the 11th European Conference on Information Systems, 2003.
[60] S. Sarker, S. Sarker, Exploring agility in distributed information systems development teams: an interpretive study in an offshoring context, Inf. Syst. Res. 20 (2009) 440–461, https://doi.org/10.1287/isre.1090.0241.
[61] B.D. Weinstein, What is an expert? Theor. Med. 14 (1993) 57–73, https://doi.org/10.1007/BF00993988.
[62] M.Q. Patton, Qualitative Research & Evaluation Methods, Sage Publications, 2002.
[63] G. Remane, A. Hanelt, R. Nickerson, L.M. Kolbe, Discovering digital business models in traditional industries, J. Bus. Strategy 38 (2017) 41–51, https://doi.org/10.1108/JBS-10-2016-0127.

[64] J. Weking, M. Mandalenakis, A. Hein, S. Hermes, M. Böhm, H. Krcmar, The impact of blockchain technology on business models—A taxonomy and archetypal patterns, Electron. Mark. 30 (2020) 285–305, https://doi.org/10.1007/s12525-019-00386-3.
[65] D.J. Teece, Business models, business strategy and innovation, Long Range Plan. 43 (2010) 172–194, https://doi.org/10.1016/j.lrp.2009.07.003.
[66] E. Ochs, Transcription as theory, in: E. Ochs, B.B. Schieffelin (Eds.), Developmental Pragmatics, Academic Press, New York, 1979, pp. 43–72.
[67] J.C. Lapadat, A.C. Lindsay, Transcription in research and practice: from standardization of technique to interpretive positionings, Qual. Inq. 5 (1999) 64–86, https://doi.org/10.1177/107780049900500104.
[68] R.K. Yin, The case study as a serious research strategy, Knowledge 3 (1981) 97–114, https://doi.org/10.1177/107554708100300106.
[69] L.P. Ruddin, You can generalize stupid! Social scientists, bent flyvbjerg, and case study methodology, Qual. Inq. 12 (2006) 797–812, https://doi.org/10.1177/1077800406288622.
[70] K. Eisenhardt, M. Graebner, Theory building from cases: opportunities and challenges, Acad. Manag. J. 50 (2007) 25–32.
[71] J.M. Corbin, A. Strauss, Grounded theory research: procedures, canons, and evaluative criteria, Qual. Sociol. 13 (1990) 3–21, https://doi.org/10.1007/BF00988593.
[72] M. Callon, J. Law, A. Rip (Eds.), Mapping the Dynamics of Science and Technology: Sociology of Science in the Real World, Palgrave Macmillan UK, London, 1986.
[73] TRUSTS, TRUSTS, 2023, https://www.trusts-data.eu/, accessed 25 January 2023.
[74] MDM Portal, MDM, 2023, https://www.mdm-portal.de/, accessed 25 January 2023.
[75] BurstIQ, BurstIQ, 2023, https://burstiq.com/, accessed 25 January 2023.
[76] German Edge Cloud, Edge Computing in der Fertigung, 2023, https://gec.io/solutions/edge-computing-in-der-fertigung/, accessed 14 February 2023.
[77] Databroker, Databroker: data Selling Documentation, 2022, https://www.databroker.global/documentation/DataSelling, accessed 25 January 2023.
[78] Health-X dataLOFT, Health-X dataLOFT, 2023, https://www.health-x.org/plattform, accessed 25 January 2023.
[79] Advaneo, Advaneo: data Marketplace, 2023, https://www.advaneo-datamarketplace.de/database/de/, accessed 25 January 2023.
[80] Advaneo, Data Spaces Solution—So funktioniert's, 2023, https://www.advaneo.de/data-spaces-solution/#, accessed 14 February 2023.
[81] Otonomo, Automotive Data, 2023, https://otonomo.io/data/, accessed 14 February 2023.
[82] T-Systems International GmbH, Telekom Data Intelligence Hub, 2023, https://dih.telekom.net/, accessed 6 November 2023.
[83] J. Schweihoff, I. Jussen, F. Möller, Trust me, i'm an intermediary! Exploring data intermediation services, in: Proceedings of the 18th International Conference on Wirtschaftsinformatik, 2023.
[84] Mobility Data Space, Mobility Data Space, 2023, https://mobility-dataspace.eu/de, accessed 25 January 2023.
[85] CDQ, CDQ, 2023, https://www.cdq.com/, accessed 9 November 2023.
[86] Snowflake, Snowflake: customer Stories: snowflake Data Cloud, 2023, https://www.snowflake.com/en/why-snowflake/customers/, accessed 25 January 2023.
[87] F. Möller, M. Stachon, C. Azkan, T. Schoormann, B. Otto, Designing business model taxonomies–synthesis and guidance from information systems research, Electron. Mark. (2021) 701–726, https://doi.org/10.1007/s12525-021-00507-x.

Ilka Jussen is a research assistant at the Chair for Industrial Information Management at TU Dortmund University. Her research interests include data sharing and incentive mechanisms to foster data sharing. She studied Logistics in her bachelor and master's degree at TU Dortmund University. Email: ilka.jussen@tu-dortmund.de

Frederik Möller is an junior professor at TU Braunschweig and a researcher at the Fraunhofer Institute for Software and Systems Engineering. His research interests include business models, design science research, data ecosystems, and incentive mechanisms to foster data sharing. Email: frederik.moeller@tu-braunschweig.de

Julia Schweihoff is a research assistant at the Chair for Industrial Information Management at TU Dortmund University. Her research interests include data sharing and the associated data sharing business models. She studied Industrial Engineering in her bachelor and master's degree at TU Dortmund University. Email: julia.schweihoff@tu-dortmund.de

Anna Gieß is a research assistant at the Fraunhofer Institute for Software and Systems Engineering. Her research interests include data sharing and focuses on the associated data spaces. She studied Industrial Engineering in her bachelor and master's degree at TU Dortmund University. Email: anna.giess@isst.fraunhofer.de

Giulia Giussani is a Digital Innovation Manager at the International Data Spaces Association. Her work focuses on data sharing and related areas such as the design of data spaces, inter-organisational collaboration and data sovereignty. Email: giulia.giussani@internationaldataspaces.org

Boris Otto holds the Chair for Industrial Information Management at TU Dortmund University and is managing director at Fraunhofer Institute for Software and Systems Engineering. His research focuses on interorganizational data sharing, data ecosystems, data sovereignty and design science research. Email: boris.otto@tu-dortmund.de