Establishing Governance Structures for Analytics-Driven Interorganizational Data Sharing Networks – Designing a Framework Based on a Qualitative Study

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Abstract. The concept of interorganizational Data Sharing in analytical applications has various benefits, especially for small and medium-sized enterprises. With the access to a broader data base, a higher data generation rate and the possible utilization of new types of data from other organizations, analytical models can be improved and new services can be implemented. However, sharing data with other organizations comes with risks and challenges. To tackle these, this work proposes an interorganizational data sharing governance framework that contains core objectives and shows organizational as well as technical fields of action that should be considered during an establishing phase of a data collaboration. To this end, a structured literature review was conducted, showing relevant research around data sharing and governance in the context of business intelligence and analytics. After that, a qualitative study – consisting of an interview series with representatives of data sharing initiatives – was conducted. With the results, a framework for analytics-driven data sharing was constructed, which was then evaluated through two workshops with domain experts.

Keywords: Data Sharing, Governance, Business Intelligence, Business Analytics.

1 Introduction and problem statement

While the application of data sharing is prevalent in vertical networks (e. g. sharing inventory data along the supply chain), its implementation in horizontal networks or even outside the own industry is the exception [1–3]. However, these are the scenarios where sharing data in the context of business analytics holds potential advantages for the involved companies [4]. Data sharing grants access to a broader data base, which can improve the accuracy of analytical models or reports and facilitate data-intensive applications, such as the training of neuronal networks [5–7]. This is particularly important for small and medium-sized enterprises (SMEs) since they naturally have limited data sources [8–10]. In addition, new and value-adding services which require data from network partners or even competitors can be established [11–13].

Related research shows that many topics need to be addressed in order to establish collaborative data sharing networks [14, 15]: On an organizational and legal level, this includes, amongst other things, data ownership, privacy, assurance of reciprocity, avoidance of opportunistic behavior and handling of strategic data assets [16–20]. Furthermore, basic technical conditions must be defined, for instance, overarching meta data and a harmonized and coordinated data structure [17, 19, 21, 22].

The mitigation of risk, which comes from opportunistic behavior, conflicts in a network or the sharing of critical business data [22], is identified by previous research as a key success factor for data sharing collaborations to work long-term [11, 18]. It can also be presumed that, according to the cost-benefit-paradigm [23], the advantages described above must outweigh the expenses for initializing and maintaining data sharing partnerships. In summary, organizational acceptance for data sharing and trust in the network structures [24, 25], which ultimately result in willingness to share data and maintaining the partnerships within the network, can be induced if the potential disadvantages are tackled adequately.

The present work proposes a governance framework to address these issues and facilitate successful data sharing in the specific context of business analytics. Here, governance refers to organizational and technical structures, processes and relational mechanisms that ensure that the governed subject – in this case data sharing – achieves the intended outcomes (which for this case are described above) [26]. The framework aims to show core objectives to ensure acceptance as well as fields of action which must be considered in the establishing phase of analytics-driven data sharing networks. Therefore, it goes beyond existing Business Intelligence and Analytics (BIA) governance structures, which typically address only a single organization [27].

The research questions are:

1. What are the core objectives to ensure trust among the involved organizations so that they are willing to share data with other organizations?
2. Which topics must be considered during the establishing phase of an analytics-driven data sharing network?

2 Foundations and terminology

2.1 Data sharing, business intelligence and business analytics

The term *Data Sharing* appears in various contexts. The idea first emerged in the 1980s, when discussions arose whether researchers should share data from uncompleted research [5]. To this day, research activity in the area of scientific data sharing is still ongoing [22, 28, 29]. Further research fields focus on data sharing in other contexts, such as the collaboration between government branches [30, 31] or within the medical sector [32, 33]. When it comes to enterprises, data sharing applications are often found in operational contexts, for example, when sharing inventory data vertically along the supply chain or providing standardized interfaces for banking data [1, 34].

Despite the existence of documented use cases in business and analytics, a definition of (interorganizational) data sharing in this context was not found in the literature review. Therefore, this work defines the term as follows:

Interorganizational Data Sharing is the cross-border exchange of business-relevant data objects among a defined group of organizations within a collaborative network. Its initiation is non-obligatory and has the intention to positively affect the business goals of the involved organizations in the long-term.

This definition of Interorganizational Data Sharing implies several points:

1. Being interorganizational, it requires more than one organization between which data is being exchanged. However, data sharing can occur within single large corporations with various (semi-)independent subsidiary organizations as well.
2. It is not a one-time exchange of data but is embedded in a long-term collaboration network with a defined group of partners.
3. Its initiation is non-obligatory. This means that data that must be shared first-hand for legal reasons (e. g. data from disclosure reports of financial institutions) is not in the scope of this definition. However, after the initiation phase, the exchange of data can be made obligatory, for example through SLAs or code of conducts.
4. It describes the sharing of data in B2B applications and therefore excludes scenarios where customers share data with organizations.

In this work, *analytics-driven data sharing* refers to use cases in scenarios within the field of BIA. This means that the business goals of the network partners are achieved via analytical methods that are typically used in BIA such as data mining methods, machine learning, online analytical processing et cetera. The term “business analytics” extends the term “business intelligence” insofar as it refers more demanding analytical approaches induced through recent use cases such as Internet of Things (IoT), Industry 4.0 or big data applications [27]. For this work however, the terms and methods typically assigned to these two terms are subsumed under BIA and therefore not strictly distinguished.

2.2 Data sharing vs. information sharing

A term that is being used in a similar context as data sharing is Information Sharing. It is thus important to distinguish between these two concepts. As stated above for the term data sharing, findings of the literature review do not provide a specific definition, nor do they distinguish between these terms. According to the common understanding in the field of information systems, data becomes information when it is put in context (semantics) [35]. Therefore, information can answer typical business-related questions, such as “Who?”, “What?”, “When?”, and is processed with the intention to solve a specific problem [36, 37].

Transferring this distinction to the field of business analytics, data is stored in the data provision layer (DWHs, data marts, data lakes) while information is generated event-related through analytical methods in order to answer specific business questions [27]. The following figure integrates the terms discussed above in the concept of business intelligence and analytics. It is important to note that the layers in the figure illustrate a logical view of BIA environments. They do not postulate separate software solutions for the elements within a layer or between layers.

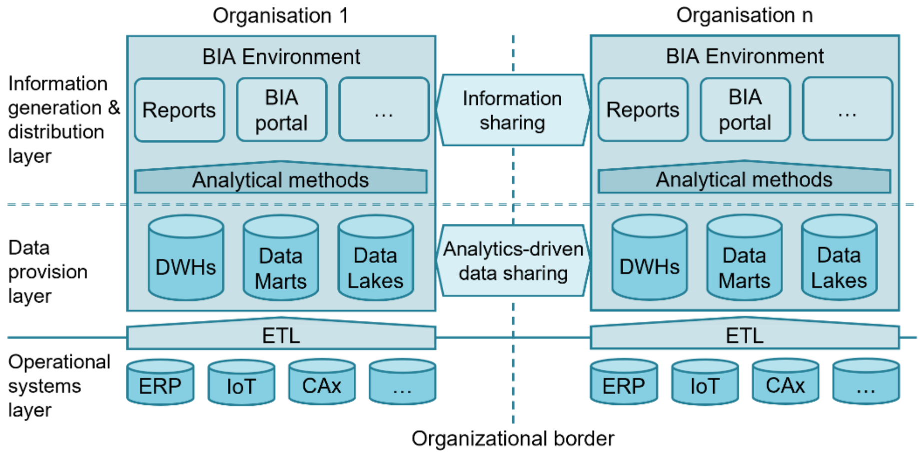

Fig. 1. Distinction between analytics-driven data sharing and information sharing as part of the BIA-framework (based on [27])

3 Research design and methods

In this work, a design-oriented and explorative approach is employed [38]. Accordingly, this research starts with the analysis phase in which a structured literature review is conducted based on [39]. This is done in order to delineate the terminology and state of research around data sharing and governance as well as draft an interview guideline.

The literature review queried several databases for the purpose of covering the most relevant journals in the field of information systems, therefore including the eight *Senior Scholars' Basket of Journals* as well as all journals ranked at least B in the *VHB-JOURQUAL3 (section information systems)* [40] ranking. In doing so, the following databases were queried: (1) ACM Digital Library, (2) AIS eLibrary, (3) Elsevier ScienceDirect, (4) IEEE Xplore, (5) informs PubsOnLine, (6) palgrave macmillan, (7) ProQuest, (8) SAGE journals, (9) SIAM journals, (10) SpringerLink, (11) Taylor & Francis Online and (12) Wiley Online Library. Depending on the capabilities of the search engine, the results were filtered in order to only show peer-reviewed literature. To further decrease the number of irrelevant results, in most cases only abstract, title and key words were considered in the search. The following table shows the search terms being used, the number of query results and the number of relevant results.

Table 1. Literature review: queried phrases and results

Query	Results	Relevant results
“data sharing” AND “governance”	50	6
“information sharing” AND “governance”	113	4
“data sharing” AND “business intelligence”	93	2
“data sharing” AND “business analytics”	42	3
“information sharing” AND “business intelligence”	4	1
“information sharing” AND “business analytics”	3	0
“collaborative” AND “business intelligence”	24	2
“interorganizational” AND “business intelligence”	1	0

Besides “data sharing”, also the similar term “information sharing” was considered. Since this paper focuses on analytics-driven data sharing, the terms “business intelligence” and “business analytics” as well as the related concepts Collaborative and interorganizational Business Intelligence (CBI and interorganizational BI respectively) were considered.

The high number of irrelevant results has two reasons: Firstly, despite searching the exact term “governance”, some search engines also considered “government”, thus leading to many results dealing with data and information being shared between government branches. Secondly, in case of data sharing and BIA, many use cases were found where data is shared within one organization. This does not meet the understanding of the concept of data sharing in this paper. After querying the databases, a reverse and forward search were conducted. The results of the literature review are being discussed in the following chapters.

With the input of the literature review and the qualitative study, whose core centered on a series of interviews with domain experts accessed through the *Industrial Internet Consortium (IIC)*, a data sharing governance framework for analytics-driven networks was generated during the design phase. Details on the interview series and the framework generation can be found in chapter 4.

The core elements of the framework were then evaluated and discussed within two workshops with domain experts as part of a research project that aims to induce analytics-driven data collaborations.

The above-described overall approach in this work is illustrated in the following figure.

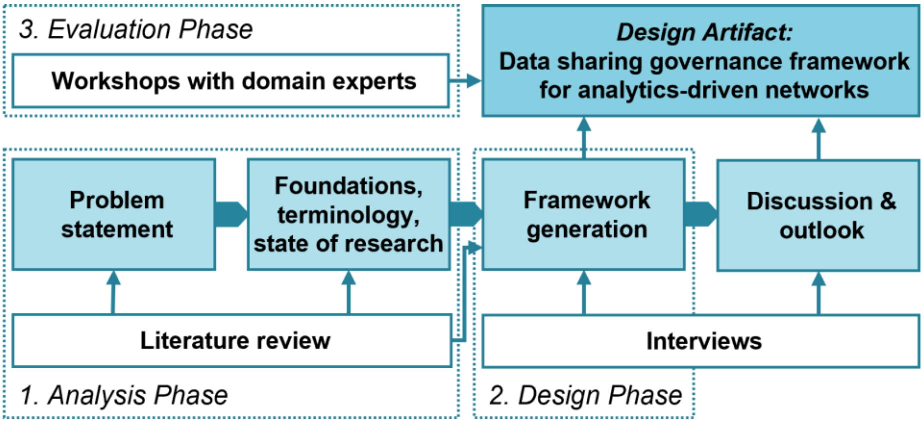

Fig. 2. Research design and methods in this work (Design Science approach based on [38])

4 State of research

4.1 Data sharing in analytical applications

When it comes to business analytics, the literature review shows that data and information sharing in analytical applications are not widespread and often based on rudimentary methods (e. g. e-mail or document exchange) [15, 41]. Still, some advanced use cases of analytical scenarios that are enriched by data sharing can be found (e. g. Collaborative Condition Monitoring [25] or Smart Farming [17]). In this context, the term "Collaborative Business Intelligence" (CBI) is used to describe internal communication, partnerships on data provision and analysis as well as (social) sharing of results (e. g. reports), in most cases referring to internal communication or technical aspects [15]. Analytics-driven data sharing, however, focuses on long-term collaboration in data provisioning and is not limited to decision support and dispositive processes as CBI usually implies [7]. Looking at the literature found in the context of CBI, most use cases are located in the field of information sharing [15] as shown in *figure 1*.

Potential advantages from data sharing in analytical applications can be classified as follows:

- **Access to higher data volume:** more data often results in more accurate decision models and is particularly important for advanced analytics methods, such as neuronal networks [7, 12].
- **Higher data generation rate:** in fast-paced environments, where models tend to outdate quickly, the fast generation of current data enables a prompt adaptation of models, therefore increasing the accuracy of such [6, 42].
- **Utilizing new data sources:** with the access to additional data sources, new analytics-based services can be introduced that require (internal) data from network partners [11, 13, 20, 25].

These points are especially relevant to SMEs due to their more limited data sources compared to larger companies [8, 10]. Therefore, data sharing has the potential to open new analytical possibilities for SMEs [8].

Regarding literature that uses the term “information sharing”, many operational applications were found [3, 18, 24, 43–45]. Since these scenarios are operational and not within a dispositive BIA environment, they are outside the scope of this study but comply with the understanding of the term “information sharing” in this work.

4.2 Governance structures for data sharing applications

The literature review shows that interorganizational collaborations within networks usually come with opposing interests of the individual organizations and, potentially, a collective goal [20, 46]. Since data is seen as an important and strategically relevant asset by many companies [47, 48], it is not surprising that network members want to mitigate risks of such a collaboration, since network partners can act opportunistic and abuse the shared data [18, 22, 25]. In the context of data sharing, recent research shows that a fair use of data and trust within a network are crucial factors for successful data collaborations [17, 20, 25, 49]. Besides trust, semantical and technical foundations (e. g. Meta Data Management [21]) need to be addressed to achieve a well-functioning data sharing environment [25, 50]. Therefore, a governance concept appears to be reasonable, so that possible issues can be prevented or resolved [20].

As part of the overall enterprise governance, IT governance refers to *“organizational structures and processes that ensure that the organization’s IT sustains and extends the organization’s strategy and objectives”* [26]. Derived from IT governance, data governance [47, 48] and BIA governance [27, 51] frameworks arose as complementary concepts. What the concepts of all these fields have in common is that they each apply to an area that needs to be governed (IT, Data, BIA) and have certain structures, processes and mechanisms that aim to ensure a desired outcome (usually strategic alignment). Applying these properties to the concept that is being discussed in this paper, here, the governed area is data sharing for analytical applications and the desired outcome is improved decision-making and the use of new data sources, while simultaneously mitigating potential risks which arise from sharing data with other companies.

An exact differentiation of the various governance concepts is not in the scope of this work, but it is apparent that a data sharing governance must point out matters which can be found in other governance frameworks as well. This overlap, however, is not a simple redundancy, but rather identifies constructs in existing governance frameworks that need adjustment when an organization is entering a data collaboration. Other than that, new issues that originate from cross-border sharing of data need to be addressed. The data sharing governance framework presented here therefore complements existing governance structures by both pointing out structures that might require adjustment and showing additional matters which need to be governed when entering a data collaboration.

5 Qualitative study and resulting data sharing governance framework

5.1 Study context and details

The qualitative, explorative study was conducted as part of a research project in which data collaborations, mostly focusing on IoT data, are established. To identify core objectives that generate a space of trust, which presumably leads to the willingness to share data, 8 semi-structured interviews with domain experts in the field of data sharing within the context of analytics were conducted. The experts were accessed through the *Industrial Internet Consortium (IIC)* and are representatives (R) of data sharing initiatives from different companies and countries. Table 2 provides an overview of the interviews.

Table 2. Overview of the conducted interviews

Rep.	Initiative	Org. residency
R1	Object tracking and analysis in logistics and supply chain	Germany
R2	Steaming and analysis of IoT data in the fishing industry	Switzerland
R3	Analytics infrastructure for device coordination in drone logistics	United States
R4	Floor planning for smart factories	Germany
R5	Optimizing plastic injection molding machines	South Korea
R6	Port traffic management	Germany
R7	Port traffic management	Germany
R8	Analytics for smart factories and smart logistics in retail	Germany

5.2 Resulting data sharing governance framework

To answer the research questions, the input from the interviews was abstracted and structured within 3 areas in the framework: The first area (*Core objectives for data sharing*) shows the main goals and therefore success factors for trust within a data collaboration, answering the first research question. The core objectives refer to the data that is shared in the network. The second (*Organizational fields of action*) and third area (*Technical fields of action*) cover the second research question by identifying the topics that must be considered while data collaborations are established. The areas are interconnected, so that the core objectives can be achieved if the fields of action are tackled adequately. However, while the framework provides content for a concrete data sharing governance, chronological information about the establishing process is the subject of further research. The distinction between organizational and technical fields of action was made to give a better overview. However, they are not dichotomous (as for example meta data management is regarded as a primarily technical issue with organizational components). Figure 3 shows the framework, which is then further described in the following sections.

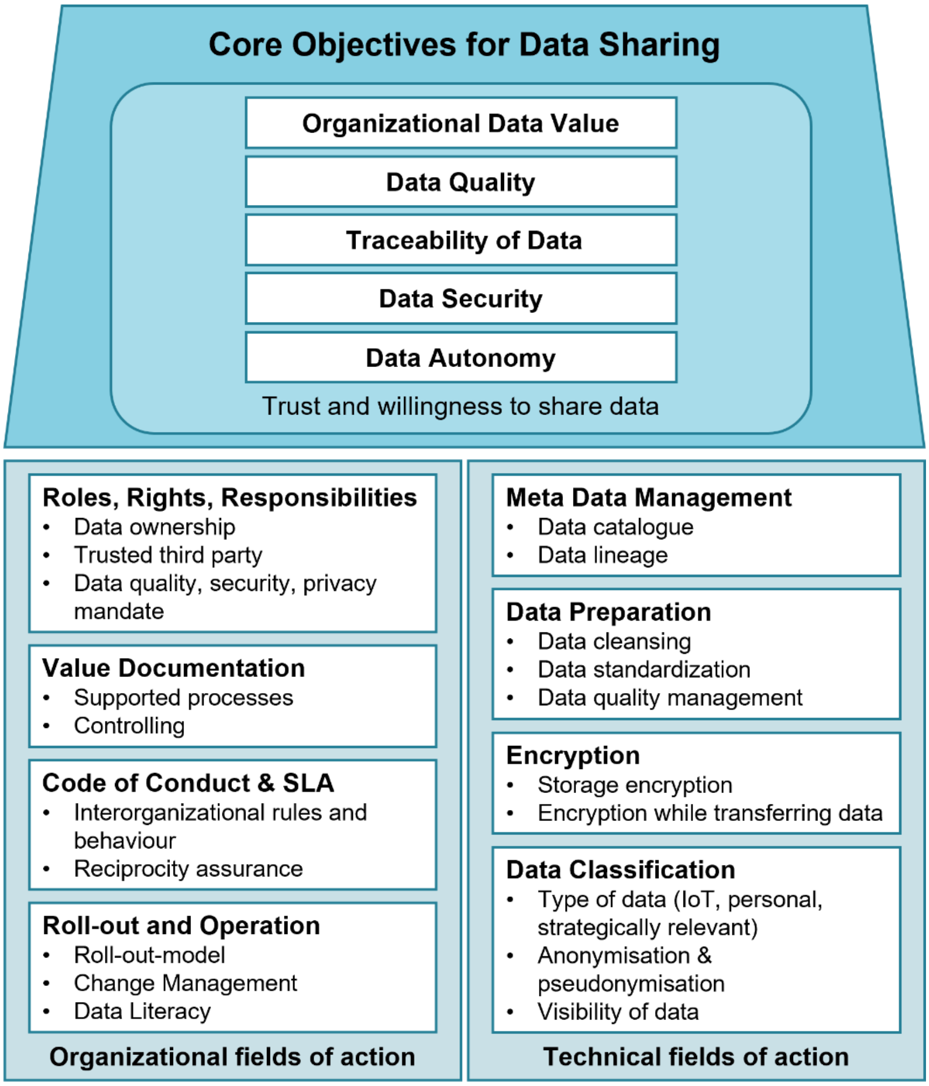

Fig. 3. Data sharing governance framework for analytics-driven networks

Core objectives for data sharing. The representatives were interviewed about the main success factors as well as potential reasons for failure of data sharing collaborations. They were also asked how a space of trust can be achieved and what hinders trust. A frequently mentioned point was that the shared data must be valuable (*Organizational Data Value*), meaning that there must be plausible use cases in further analysis [R1, R3, R4, R8]. For an efficient application, the shared data used for further analysis must be reliable and suitable for the intended purpose. In other words, the *Data Quality* needs to be on an adequate level [R2, R8], which is often part of data governance frameworks [47, 48, 52]. A crucial point of trust in the network is the *Traceability of the Shared Data*. This means that mechanisms that enable transparency by showing where the data of the individual network partner is being employed should be considered. These mechanisms could help participants to comprehend for what specific analytical applications their data is being used by their network partners, thus mitigating the risk of abusive behavior from the other members of the network [R4, R7, R8]. While maintaining *Data Security* is a vital part of a regular data governance [47], this matter is especially emphasized in data sharing scenarios due to the fact that data is leaving the own enterprise's boundaries [R1, R2, R8]. Finally, the last core objective is to stay on an adequate level of *Data Autonomy* for the involved organizations, meaning that the providing organizations retains control over their own data [53] – at least for specific types of data (e. g. strategically relevant business data) [R1, R3, R4, R8].

Organizational fields of action. The following fields of action focus on managerial aspects, where concrete technical implementations are secondary.

The section *Roles, Rights, Responsibilities* targets multiple objectives, mainly data quality, security and autonomy. As data is shared between organizations, data ownership is a recurring topic, a fact that was also reflected in the interviews. Here, an overarching and transparent concept that specifies which party owns the rights for which data object was identified as crucial for the willingness of participants to share data [R1, R3, R4, R8, 25]. When setting an architectural design for a data sharing environment, getting a trusted third party involved might be considered (e. g. for overall coordination, data storage et cetera), since the neutrality of this party is more likely. This could reduce the chance of opportunistic behavior, possibly resulting in the involved organizations to be more open to share their data [R6, 11]. Another recurring remark was that clarifying the responsibilities for these highly relevant topics – data quality, security and privacy – is helpful as they become neglected when no clear mandate is defined and assigned [R1, R2, R8, 48].

Value Documentation describes the need to point out business cases, showing how the shared data can be utilized for certain business goals [R1-4, R6, 25]. This includes the documentation of how data sharing supports processes within a company, thus increasing transparency and ultimately giving value to the data [R1, R6]. This also means that the company's (IT-)controlling needs adjustment, so that it considers the value of data sharing and supports cost transparency of the use cases. This is important in order to make the organizational data value visible, therefore enabling cost-benefit-calculations [R1-4, R6].

Code of Conducts & Service Level Agreements (SLA) are two mechanisms that can ensure reciprocity and reduce opportunistic behavior, so that the space of trust remains intact [R1, R3-5]. A code of conduct is a set of overarching and generalized rules of behavior which are based on collective values. It lays the basis for further and more detailed guidelines and rules [54] and can be implemented in (semi-)formalized ways or, when not explicitly documented, still shows in an informal way. The latter is presumably suitable for collaborations where a solid space of trust is already present. SLA, however, are detailed documents that state which type of data is shared in which specific frequency, quality and quantity [R1, R8].

In the context of *Roll-out and Operation* of the data sharing collaboration, actions that ensure management sponsorship and staff support should be considered [R4, R7]. One of them is to select a suitable roll-out model (incremental, big-bang et cetera) that fits the preferences of the organization's staff. Like in other initiatives, Change Management activities should be considered as they affect the success of the implementation of organizational change [55]. Due to the larger volume of data which comes from an increasing amount of data sources, the concept of Data Literacy becomes relevant as it serves to get the most value out of the shared data [56]. Thus, when entering data collaborations, adequate personnel development in data literacy should be considered, so that the shared data can be used effectively and efficiently [56].

Technical fields of action. This section describes fields of action which are implemented by technical solutions but are mostly triggered by business needs (e. g. meta data, data classification et cetera).

One key aspect is the *Management of Meta Data*, which is required for an effective and efficient use of the shared data [27]. In this context, meta data is used to describe the semantics and syntax of the shared data, which is a key requirement for integrating it in one´s own analytical application and for having an overarching business understanding of the shared data [R2, R8, 47, 48]. One suitable concept, therefore, is a coordinated Data Catalogue, which structures the shared data and provides user-friendly access to a single point of truth [48]. Another concept that should be considered in this context is Data Lineage, which aims to give a transparent overview of what data is used for what kind of use case or analysis [48]. This particularly serves as the core objective of data traceability.

Data Preparation contains mechanisms that ensure that the shared data is suitable and usable for analytic purposes. While data quality management, which comes with data cleansing, is often mentioned when it comes to data governance, it becomes an especially challenging task when several organizations are affected, as it requires the data quality and cleansing process to be coordinated for all involved companies [R2, R8, 47, 48]. In addition, data standardization is a key requirement for an overarching view on the data across many individually managed data sources [57]. To minimize the effort of data cleansing in big data environments, automated procedures should be considered [R8]. Also, formalized data quality agreements can be helpful in shared data networks [R8].

The *Encryption* of data during its storage and transfer serves data security and is considered a basic, yet important criteria in data sharing collaborations as well as in regular data governance [R1, R2, R8, 47]. However, this matter is particularly essential when data is being transferred to other organizations, especially when dealing with crucial data (e. g. customer data, strategically relevant data) [R1, R2]. Therefore, the encryption of data should be considered when setting up data collaborations.

With *Data Classification*, mechanisms for differentiating data (e. g. IoT, personal, strategically relevant) should be taken into account as different types of data mostly have different value to organizations, which means that they need to be treated differently [R1, R7]. Furthermore, most organizations presumably are not willing to share all their data [R1, R7]. With the possibility of data classification, further questions arise regarding authorizations and visibilities – What data can only be shared anonymized or pseudonymized and which type of data is visible for which network partners? [R1, R3, R7] These questions, however, are closely related to the roles, rights and responsibilities concept, as it should give an answer to the question: “Who (organization) sees what (type of data)?” Also, the classification of data serves as the core objective of data autonomy as it provides the possibility for the data owning organization to decide which type of data is shared with whom in which way (e. g. anonymized).

6 Discussion and outlook

The presented framework contributes to the research area of data sharing in the context of business analytics. The literature review and the interviews made clear that data sharing comes with relevant practical, organizational and technical issues that need to be addressed through governance structures. Derived from an interview series and enriched with literature, the here presented framework gives an approach and lists fields of actions which need to be tackled in the establishing phase of a data collaboration, therefore answering the research questions mentioned at the beginning.

The here presented work comes with limitations. A frequently mentioned aspect was that a collaboration needs to ensure a trustworthy environment, where fear of opportunistic behavior is minimized. While there are several points where topics related to information systems can support this goal (as shown in the framework), data sharing must be looked at from an interdisciplinary stance. The reason for that is that things like the overall competitive environment, political conditions and character traits of deciders within the companies can play a relevant role in their willingness to share data. Furthermore, because the framework was mainly derived from an interview series with experts having experience with data sharing initiatives in the field of IoT data, it cannot be generalized. More studies, long-term use cases in other contexts and further evaluations are needed to verify and strengthen the framework. While the framework provides contents of a concrete data sharing governance, chronological information about the establishing process is not given here and therefore up to further research.

BIA solutions within single organizations are widespread, data sharing applications however are rather niche. It is not farfetched and agrees with statements made in the interviews that this has presumably to do with data sharing coming with risks, something that usually needs justification in companies. Therefore, value documentation and the recognition of the possibilities of data sharing networks are crucial. For this to happen, more research and use cases are needed to show the potential of such an approach. Moreover, the success factors of data sharing need further investigation. Within the fields of action, more research is needed that show which option under which circumstances is suitable. It is also likely that other success factors of data collaborations apply that were not treated in this work.

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