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THE DATA COLLABORATION CANVAS: A VISUAL FRAMEWORK FOR SYSTEMATICALLY IDENTIFYING AND EVALUATING ORGANIZATIONAL DATA COLLABORATION OPPORTUNITIES

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Research Paper

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Abstract. For organizations, the use of Big Data and data analytics provides the opportunity to gain competitive advantages and foster innovation. In most of these data analytics initiatives, it is possible that data from external stakeholders could enrich the internal data assets and lead to enhanced outcomes. Currently, no framework is available that systematically guides practitioners in identifying and evaluating suitable inter-organizational data collaborations at an early stage. This paper closes the gap by following an action design research approach to develop the Data Collaboration Canvas (DCC). The DCC was rigorously evaluated by practitioners from Swiss organizations in six different industries, instantiated in four workshops, and used to guide innovative data collaboration projects. This artifact gives practitioners a guideline for identifying data collaboration opportunities and an insight into the main factors that must be addressed before further pursuing a collaborative partnership.

Keywords: data sharing, data collaboration, DSR, canvas.

1 Introduction

Organizations are now aware that their data assets can potentially provide an additional value stream, enabling them to remain competitive in their environment (LaValle et al., 2011). Even data collected in the past might provide value for new products and innovations (Constantiou and Kallinikos, 2015). Additional value could be realized by combining data from different sources into data-based products, which satisfy market requirements better than each part alone (Günther et al., 2017). To identify valuable data assets, it is crucial to expand human expertise within the organization and have easy access to the available data (Seddon et al., 2017). This is why organizations have started to extend their strategy toolbox and use data analytics to understand and better utilize their data assets (Woerner & Wixom, 2015). These data analytics initiatives also provide information about the weaknesses within existing data assets; such weaknesses can stem from low-quality data, internal data silos, or a missing data governance structure (Mikalef & Krogstie, 2018). Data analytics can help increase data accessibility by cleaning, normalizing, and centralizing the data (Dinter, Schieder & Gluchowski, 2015).

It can also be observed that large corporations have introduced new data governance structures, for example, the role of Chief Data Officer and data governance boards to safeguard valuable assets and oversee the competitive features of these assets (Otto, 2011; Ladley, 2012). Organizations have also realized that they have data blind spots within their assets. Such missing data features cannot be easily acquired, and other strategies are needed to gain access to these missing data so as to keep up with larger tech companies (Gulati & Singh, 1998). An example of a data blind spot might be a small retail company that has data about the shopping behavior of its customers but has no knowledge about the additional items that would complement a customer's shopping basket. In comparison, large tech companies like Google, Amazon, Facebook, Apple, and Microsoft have data assets providing intelligence about customers in a variety of areas (Miguel & Casado, 2016). It is clear that this competitive disadvantage can be an obstacle for small organizations, which is why some operations have started to form collaborative data initiatives (Pouwels & Koster, 2017). Similar to data initiatives within a single organization, it is important to clarify important aspects of inter-organizational data collaboration.

Several visual artifacts have been described in the recent literature to systematically guide the development of data initiatives within a single organization (Thoring, Mueller & Badke-Schaub, 2019). However, to our knowledge, a systematic framework to facilitate inter-organizational data collaboration at an early stage is currently missing. Therefore, this paper will address the following research question: *"How can a visual artifact facilitate the identification and systematic evaluation of data-based, organizational collaboration?"*

To answer this question, this paper will first provide an overview of related visual tools and data-based organizational collaboration (Section 2). The research method is explained afterward, followed by a presentation of the "data collaboration canvas" (DCC). Finally, we examine the iterative evolution and instantiation of this novel artifact in an organizational environment and discuss its impact and limitations.

2 Foundation and Literature Review

Different theoretical perspectives have been described to explain the formation of inter-organizational relationships (Barringer & Harrison, 2000). These relationships are typically initiated to create additional value for the participating organizations (Liu and & Zou, 2019). Mitchell and Singh (1996) described as one possible reason for forming inter-organizational relationships, that the access to critical resources can be essential since it helps gain market power by filling a resource gap. Related to data-based organizational collaborations, this resource gap can be the deficiency of a data asset that can be remedied by fostering inter-organizational relationships to share data (Richter & Slowinski, 2019). Such a relationship could also involve several different partners to create an entire data ecosystem (Oliveira et al., 2018). Not only resource dependence but also the theoretical perspective of organizational learning could explain the formation of inter-organizational relationships. Powell et al. (1996) wrote that organizations could have a competitive advantage if they interacted to share knowledge. To form a data-based collaboration, it is necessary to share knowledge about data assets and be open-minded concerning the data and processes of the other organizations. This external view on data assets could also promote innovation within the relationship supported, for example, by creativity workshops (Polewsky & Will, 1996). To guide a knowledge-sharing process, visual tools such as the business model canvas (BMC) by Osterwalder et al. (2010) have shown their effectiveness in helping to systemize the development of new ideas and help focus on key areas during ideation (Avdiji et al., 2018). As this work focuses on the determination of a visual tool to support data collaboration, we conducted a literature review to determine what visual artifacts are currently available and what are important aspects for formation of data collaborations. The search terms “data collaboration”, “data sharing”, “data ecosystems”, “business ecosystems” and “digital platforms” were each combined with the search term “canvas” and used within the databases Proquest and Web of Science. The search resulted in a total of 748 (690 without duplicates) publications within the last five years of which 63 were of interest based on the title and on the abstract of the publication. Based on our search terms we could not identify a canvas that facilitates data collaboration projects in an early stage. Recent work by Krasikov, Eurich & Legner (2021) support this view and propose a reference process for data sourcing and managing external data. Nevertheless, we could identify several aspects that are of relevance for data collaborations. The literature on inter-organizational data collaboration highlights that the potential of data ecosystems or collaborations is still not realized (van den Broek & van Veenstra, 2015). The main challenges that are identified are in the area of data governance (Abraham, Schneider & vom Brocke, 2019). Organizations still struggle to ensure data ownership and control in inter-organizational relationships. These properties have to be clarified as early as possible to enable a commercially successful collaboration. As a prerequisite it is recommended that organizations clarify for themselves what data is available, who is responsible for the data, how this data is produced, used and under which conditions this data can be shared (Lis and Otto, 2020). Data catalogs can help to describe these aspects of internal data (Labadie et al., 2020). But it is still unclear how a commercially viable model for cross-organizational data sharing can be set up (van den Broek & van Veenstra, 2015). There are already artifacts that have been useful for organizations to understand internal data initiatives (Sammon & Nagle, 2017), facilitate ideation with data (Kronsbein & Mueller, 2019), and support the identification of data service systems (Hunke, Seebacher & Thomsen, 2020). Sammon et al. (2017) observed that data-based value creation within internal data initiatives needs a shared understanding and a common participant language. These properties are also necessary for developing new data-based ideas between two organizations as a shared understanding and language cannot be taken for granted. A shared understanding of each other's strengths and weaknesses can also result in unexpected opportunities for new data-driven products (van den Broek & van Veenstra, 2015). Hernandes et al. (2022) analyzed frameworks for data ecosystems and highlight that in addition to the above interoperability of the organizations and possibilities for data fusion (combination) is important. Kamariotou and Kitsios (2022) extended the BMC to open data ecosystems and determined that for the value proposition within the ecosystem the resources and activities of the partners as well as the incurred cost and revenue is important to determine. Similar findings have been determined for big data-based business models (Wiener et al.2020). From the employee perspective Förster et al. (2022) found that the cost of the data is not relevant but the value that can be generated with the data.

During our exchange with practitioners from various Swiss-based organizations it became clear that practitioners have the need for a visual artifact to facilitate communication between two organizations in core areas related to the systematic evaluation of data collaboration. This paper will address this shortcoming by developing and testing a visual canvas to guide the early stages of a data-sharing partnership.

3 Methodology

Our approach to developing the DCC follows the action design research (ADR) method (Sein et al., 2011). The technique is best suitable in situations where the research process of building, using, and evaluating the artifact is shaped within the organizational context (Sein et al., 2011) and follows four stages; the first three can be iteratively cycled.

First, the problem was formulated as a research question based on initial exchange with practitioners and the current literature on data-based collaborations. Here, we followed the recommendations of Avdiji et al. (2018) to create tools for poorly structured problems. The issue was framed using an ontology. The ontology was used to create a visual representation in the form of a canvas. In the second stage of the ADR, the artifact was evaluated and shaped based on expert feedback and current literature on visual collaboration artifacts. The second stage included two additional iterations, and each evolutionary phase was followed by a reflection and learning phase. The output of expert workshops and individual practitioner interviews was used to optimize the understandability and usefulness of the framework. The complete iterative process took eight months, from March – October 2021 (Table 1). During this timeframe, five workshops ranging from 2–5 hours evaluated the DCC. The workshops started with a short introduction of the DCC. The participants used the DCC in a second phase to identify and evaluate data opportunities. In the last phase of the workshop all participants gave feedback to the understandability and usefulness of the DCC. The researchers took pictures during the workshops and collected the written feedback. In addition, nine individual expert interviews, ranging from 1–2 hours each, were conducted online using the respective version of the DCC. Two senior researchers conducted the semi-structured interviews, but because of confidentiality concerns of the experts, the interviews were not recorded. The interviews addressed first the understandability of the canvas. In a second phase the interviews addressed possible missing points within the current instance of the canvas. Following the interviews, these two researchers noted the critical insights from the discussion and possible adaptions to the artifact. The specialists from different industry sectors in Switzerland, including banking, mobility, retail, and insurance, all had roles (e.g., Chief Data Officer) associated with innovation or data processes within their organizations. We deliberately invited specialists from different industry sectors to get a consensus view on the artifact.

Table 1: *Schedule of the DCC iterations with partners (I.: Iteration)*

	Date	Partner	ID	Industry	Time (h)
I.1	23.03.21	Workshop (26 Participants - 4 Groups)	W1	Multiple	2
I.2	16.04.21	Interview w/ Business Analyst	P1	Insurance	1
	26.04.21	Interview w/ Data Scientist	P2	Insurance	1
	30.04.21	Interview w/ Chief Data Officer	P3	Retail	1
I.3	19.05.21	Interview w/ Innovation Manager	P4	Banking	2
	26.05.21	Interview w/ Data Scientist	P2	Insurance	1
	26.05.21	Workshop (4 Participants - 1 Group)	W2	Multiple	1
	07.06.21	Interview w/ Chief Data Officer	P3	Retail	1
	16.06.21	Interview w/ Head of Data	P5	Mobility	1
	17.06.21	Interview w/ Innovation Manager	P6	Insurance	1
	28.06.21	Interview w/ IT Architect	P7	Postal Service	1
	29.06.21	Workshop (20 Participants - 3 Groups)	W3	Multiple	2
	07.09.21	Workshop (16 Participants - 2 Groups)	W4	Multiple	2
	20.10.21	Workshop (10 Participants - 3 Groups)	W5	Multiple	5

The current version (I3) of the DCC was evaluated in two online workshops (20 and 16 participants, respectively) and an in-person workshop with ten participants (Table 1, W5). Workshop participants always successfully identified novel data collaboration opportunities using the DCC and provided rigorous feedback on the usability and usefulness of the current artifact. The DCC was used by practitioners, as described in Section 5.3, to successfully identify a data collaboration between two organizations and derive a feasible IS/IT alignment (according to Stolze et al. (2011)) to implement the opportunity now used in production.

4 The Data Collaboration Canvas

The following paragraphs describe the DCC in greater detail. The framework is organized into two parts; each part has different components identified as relevant based on the current literature and expert practitioners interviewed during the iterative ADR evolution stages. It is worth mentioning that in Figure 1, we show a possible collaboration between two organizations. Still, it is also possible that the collaboration partners are organizational units within one organization. It is potential also possible to extend the canvas to include more than two collaborators.

4.1 Idea Generation within the Data Collaboration Canvas

The idea generation part of the DCC (Figure 1) is tailored to help identify valuable opportunities for collaborations between organizations ("data collaboration opportunities").

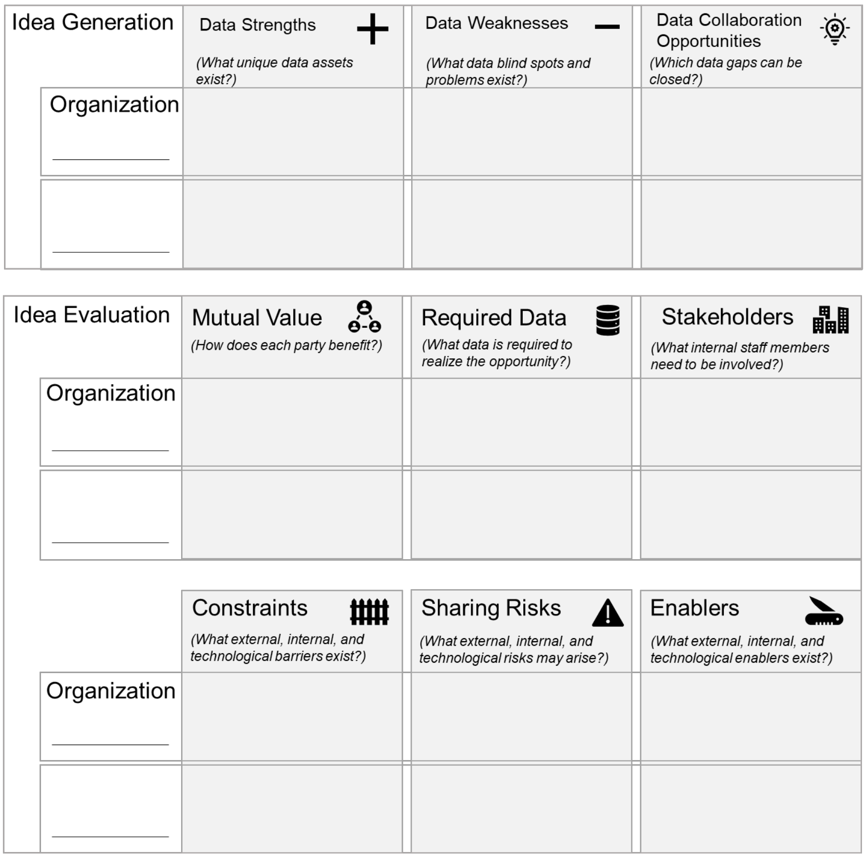

Figure 1: *The DCC is used to identify (Idea Generation) and to structure (Idea Evaluation) collaboration opportunities.*

Specifically, this part of the canvas addresses the theory of resource dependence (Mitchell & Singh, 1996), as it aims to fill the potential resource gaps of the organizations. During the process of forming a data collaboration it is an optional first idea generation artifact that can identify unique complementary data assets, whose combination could result in a data collaboration opportunity. This part of the DCC also fosters open innovation, as described by Enkel et al. (2009), because both organizations are invited to discuss data weaknesses and strengths openly.

Data strengths: Within this component, each participant in the possible data collaboration must note the available datasets unique to the respective organization. For example, a retailer has information about the shopping baskets of its customers as well as addresses and personal interests. This part of the canvas follows the data-driven approach, where data are of the highest importance, and organizations should first identify their valuable assets (Dinter & Krämer, 2018; Hannila et al., 2019).

Data weaknesses: This part of the canvas highlights areas where an organization has weak spots within its data assets. For example, a retailer does not know where its customers buy other items, so it may be interested in having a complete view of the shopping basket of its customers and extending its portfolio. As for data strength, it is also essential to identify and close gaps within the data assets to improve organizational performance (Kaufmann, 2019).

Data opportunities: As shown in Figure 1, a simple cross-over of the strength and weakness box can be used to identify areas where the strength of one participant matches a weakness of the other. These areas are called "data collaboration opportunities" and can be termed as such within this component.

4.2 Idea Evaluation within the Data Collaboration Canvas

To form a relevant collaboration between the participating organizations, a collaboration opportunity that provides mutual value for the participating stakeholders is needed (Osterwalder & Pigneur, 2010). This value can be seen as a competitive advantage for the individual members (Provan & Kenis, 2008). As this collaboration is data-based, it requires data that the stakeholders can share. Hence the mutual value, stakeholders, and required data are the central components of the ontology. The data collaboration opportunity is the central entry point into the ontology (Figure 2).

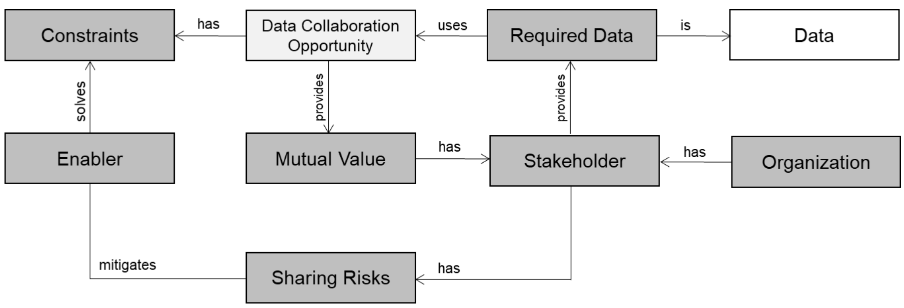

Figure 2: Ontology for the idea evaluation part of the DCC.

The organization's stakeholders have to manage the risks of sharing internal data (Meyer, 2018), while constraints hinder the data collaboration opportunity since, otherwise, it would already exist (Tona et al., 2018). To mitigate these constraints and risks, new enablers have to be identified (Sonehara, Echizen & Wohlgemuth, 2011).

Avdiji et al. (2018) recommended that the ontology be visually represented to enable collaborative ideation, and this visual representation is presented in Figure 2. The idea evaluation part of the DCC can be used independently of the idea generation part as it anticipates only a known data collaboration opportunity from the participating organizations. During the process of forming a data collaboration this opportunity could have been created within the idea generation part of the DCC or already developed elsewhere. The idea evaluation part focuses largely on the early and systematic evaluation of this opportunity and can be seen with the theoretical lens of organizational learning (Powell, Koput & Smith-Doerr, 1996). This helps to facilitate knowledge exchange as early as possible, generates a common understanding of the opportunity, and focuses on the most relevant areas that should be clarified before investing in developing the respective data opportunity. During the ADR iterations, these theory ingrained areas emerged as most pertinent to align IS/IT according to Stolze et al. (2011) and need to be clarified by the organizations involved.

All components of the idea evaluation part of the DCC are split into two areas that correspond to the two organizations participating in the collaboration. This enables both parties to note down their information for the component at hand. In addition, if other organizations participate in a collaboration, it is possible to have three or more areas per component thanks to the DCC's easy extensibility to accommodate multi-party involvement.

Mutual value: This component describes the benefits and motivations for data collaboration. Data collaboration requires that all organizations benefit from it, for example, through monetary compensation or data exchanges. Benefits could also be related to offering customers new or better services or improving an organization's reputation. This part of the canvas was significant for all practitioners interviewed during the evolution phase and was highlighted by Osterwalder et al. (2014) and Wiener et al. (2020).

Required data: This component holds detailed information concerning the data used. Based on the opportunity generation stage, an initial idea of the data required is typically already available (e.g., customer location data) and is specified in more detail here. For example, ought the data to be granular (e.g., customer records) or at a more aggregate level (e.g., statistics)? The answer will influence subsequent concerns such as risks and constraints. If personal data are needed, this might require additional customer consent. As Kayser et al. (2019) remarked, there can be a variety of data assets, but it is vital to specify precisely the data required in the shared context.

Stakeholder: This component holds all information related to the stakeholder(s) necessary to proceed. These can be internal departments such as marketing or operations and support functions such as IT, legal, or risk management. Stakeholders could also be external vendors. This component also helps to assess the alignment needed between business and IT, as noted by Sabherwal et al. (2019).

Constraints: This component describes what currently prevents data owners from sharing these data. Constraints are typically technological (e.g., no software interface existing), internal (e.g., no processes exist), or external such as data privacy and security (e.g., competition, legal regulations). As Tona et al. (2018) mentioned, ethical reasons could be a constraint for collaboration, underlining the importance of discussing this area at an early stage.

Sharing risks: This component describes the risks for parties in realizing the data sharing opportunity. Fang et al. (2017) and Meyer (2018) both described examples of risks, including data breaches or other breaches of confidentiality, adverse effects on reputation, illegal cooperation (e.g., breaches of antitrust law), and poor-quality data.

Enabler: This component records potential enablers for this data collaboration opportunity. Enablers are typically technical (e.g., secure data transfer, data anonymization), organizational (e.g., non-disclosure agreements, certificates, insurances), or based on the environment (e.g., third parties, legal regulations), as shown by Geppert et al. (2022) and Liu et al. (2019).

5 Evolution

The main discoveries revealed during the evolution of the DCC are shown in Table 2 below. The workshop participants identified data collaboration opportunities and gave rigorous feedback to the usability and usefulness of the current artifact. Details of this feedback is given in the following paragraphs.

Table 2: Conclusions from the evolution leading to the current DCC.

	Iteration 1	Iteration 2	Iteration 3
Conclusion	Iteration 1 was useful to start the idea-generation process. It showed clearly that IT/IS alignment is needed for a common understanding of the idea.	The interviews highlighted the need for a common language for practitioners. It became increasingly clear that an additional idea generation section is needed. The discussion also showed that the areas are already helpful in mapping out a collaboration but could be simplified.	The experts could easily understand the components of the canvas and structure collaboration opportunities using the canvas. Within the workshop setting, the participants could generate and validate opportunities, offering compelling evidence for the usefulness and usability of the DCC.

5.1 Iterations 1 & 2

Version 1 of the DCC was created based on the current data collaboration literature and shaped in an initial workshop with industry participants. Based on experiences and feedback from this first workshop, a second iteration of the DCC was generated, and this version was discussed with industry experts to evaluate its comprehensibility. It was clear to the experts involved that business value is a critical component and that risks concerning compliance, privacy, and legal issues must be resolved as early as possible.

During the interviews, it became apparent that the organizations were searching for innovative opportunities and needed an additional phase to create potential opportunities. One interviewee commented: “There are always two phases; first you have to identify a partner and then you can evaluate” [P3]. The need for open innovation was also mentioned during the same interview: “We know our assets and can identify partners based on our weaknesses, but this is always driven based on an inside view. Real innovation would first need an open exchange of relevant assets.” [P3]. It was also stated that one should start with the value of the opportunity: “There has to be a mutual benefit. Something should come out of the collaboration, and this needs to be discussed first” [P2]. It was apparent during all the interviews that the wording also needs clarification and should be adapted to industry practice. Regarding an early naming of the data collaboration opportunity, one expert articulated, “we would not call the input for evaluation a use-case; it is a possible opportunity” [P4].

5.2 Iteration 3

Feedback from Version 2 was used to further shape the ontology (Figure 2) and the canvas (Table 2). The updated canvas became the idea evaluation part of the DCC (Figure 1), and an additional idea generation part was added to the DCC (Figure 1). This section addresses the need to identify relevant collaboration partners not addressed in the initial design. This latest version was then rigorously evaluated in interviews with specialists as well as in several workshops. The main findings were that experts could easily understand the different areas of the canvas and also grasped the two-step process (Table 2). Indeed, they all saw additional value in the DCC and could imagine a setup for using the canvas within their organizations. Some participants were already using the DCC to structure workshops and present collaborative projects to management for go/no-go decisions.

The idea generation part of the DCC was seen to be extremely useful in itself: “It is interesting to note which unique data we possess and where we miss information” [W5], and useful to facilitate an early-stage discussion of a collaboration: “This seems to be very useful in an early phase of discussions” [W4, P6]. The second part of the canvas was seen to be helpful in structuring a possible collaboration opportunity: “I have the feeling our current work is very unstructured; this would help us structure our process” [P6].

The workshop evaluation gave additional insight into the usability of the DCC. In a short time, participants could always find initial possible opportunities and evaluate them on the DCC. They stated that the canvas was very compelling and gave an interesting insight into the assets of different industries in a short time. It was found to support and guide the discussion and help cover the key areas first: “Very comprehensible, and the canvas covers all important aspects” [W5], “Very good as a basis for further discussions; easy to identify the initial opportunity based on the field structure” [W5].

It was also stated that the initial workshop results could easily be verified with internal stakeholders to clarify all the open issues identified and then move ahead following clarification: “Both companies get a checklist for internal clarification, which reduces the number exchanges that we would need if we didn’t structure the opportunity” [W2].

This was seen to be valuable as it reduces the cost of an initial proof of concept. The participants were also pleasantly surprised that they could identify and clarify complex cases in such a short time when using the canvas.

5.3 Using the DCC

The following procedure can be followed when instantiating the canvas in a workshop setting. This procedure was tested in workshops in an online setting (Table 1, W1-4), where all participants had access to a shared whiteboard application, and in a physical setting, where all participants had access to real whiteboards (Table 1, W5). All participants got the canvas and a booklet with additional explanations for their personal preparation. The workshops were structured – in line with the canvas structure – in two phases. In the first phase, participants from several different companies, previously unknown to each other, were invited to complete the first part individually.

Following this individual think-phase, the participants were placed in pairs to see if relevant opportunities could be derived by comparing the individually identified strength and weaknesses. We called this part of the workshop "data-driven speed dating" because participants came together for a short amount of time to compare their strengths and weaknesses, identify possible opportunities for future collaboration, and then moved on to the next brief encounter.

Based on the opportunities identified, the second part of the workshop could now begin. In this phase, the DCC facilitates the systematic evaluation of individual collaboration opportunities and enables an assessment from the perspective of two or more participating organizations. Representatives of the different companies involved in the data opportunity completed the second part of the DCC together. Here, they discovered whether the collaborative opportunity was feasible and ought to be discussed further within the organization or discarded altogether (e.g., because no mutual benefit existed). Additional internal and external experts (e.g., legal, risk, and IT departments) can also support this process. Participants were preassigned to a group of 3-6 persons within the workshops, and each group decided which was the best opportunity identified by the phase one pairings. In phase two, only the opportunity selected was evaluated by the entire group.

Two industry partners (a bank and a postal service provider) applied the procedure mentioned above. In this example, a data collaboration opportunity was identified based on the first part of the DCC and then evaluated using the second part of the canvas. In the idea generation part of the DCC, the bank had a data weakness in that up-to-date customer addresses were not always available and that because of this, mailings were not always delivered, thereby increasing the cost of client interaction. The postal service prover had a unique data strength because it offered services to update incorrect customer addresses. As the industry partners were from banking and postal services, several legal constraints were identified in the second part of the canvas; however, these could be mitigated by using novel privacy-enhancing technologies as an enabler. Since all areas were clarified at an early stage (such as finding the stakeholders needed to reduce the risks), the project could be successfully started. The results were incorporated into a white paper for industry experts in the field of data innovation. This white paper – which contains additional information about the use of the DCC and the use-case as a working example – will also be released to the wider practitioner community.

6 Discussion

This paper presents the DCC – a visual framework to facilitate data collaboration between organizations or organizational units within the same organization. As this framework provides a new solution for a practical problem, the ADR approach was followed during its creation (Sein et al., 2011). The benefits of the DCC are twofold: First, it can help identify possible collaboration partners and, second, it determines very early in the process of forming a collaboration the most beneficial of those opportunities and can lead to maximization of the data value (van den Broek & van Veenstra, 2015).

The DCC also helps balance the focus of discussion between collaborative partners to the most relevant areas for data sharing (Reich & Benbasat, 2000; Sabherwal et al., 2019). Using the DCC, organizations can develop very early a shared understanding of data-based opportunities, helping them form a mental picture of the final project. This also helps to spot potential flaws, which can be clarified together. The design of the DCC incorporates the language of industry experts and aids practitioners in finding a shared language. The structure of the DCC guides the user through a conversation process that assists in speedily overcoming misconceptions and identifying relevant information regarding the opportunity.

The research described in this paper follows the ADR paradigm and, as such, has certain limitations that need to be acknowledged. The artifact is derived from the scientific literature, and the current version has emerged from several workshops. While this is the standard approach to ADR, it would be beneficial to validate the derived components of the DCC further. Additional workshops would be necessary to assess further the applicability of the framework for small and medium enterprises. A further potential weakness stems from the personal involvement of the researchers in the workshops. Although this is a common feature of action research, such participation could have biased the results of the workshops. To some extent, the expert interviews may have redressed this possible imbalance. Nevertheless, the first application of the DCC in a project within an organization shows it can be applied without the researchers' direct involvement. This paper does not focus on forming open data initiatives, which have also been studied, for example, by Conrado et al. (2017). It is evident, however, that the use of open data could further enrich an inter-organizational collaboration.

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