6-18-2022

Collaborative mechanisms for big data analytics projects: Building bridges over troubled waters

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COLLABORATIVE MECHANISMS FOR BIG DATA ANALYTICS PROJECTS: BUILDING BRIDGES OVER TROUBLED WATERS

Research Paper

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Abstract

Big data analytics (BDA) is accepted to be an important driver of business value. Deriving value from big data to improve organizational decision-making requires the collaboration of data science experts and business users. However, recent literature has shown that their relationship is troubled. Tension arises from diverse relational difficulties and change-inherent challenges. The relationship has been theorized to lack social capital, which leads to inferior collaboration and diminishes project success. In this vein, scholars have begun to investigate relational governance mechanisms, but detailed insights on collaborative approaches to foster the relationship remain scarce. By applying multiple-case research, we shed light on collaborative mechanisms and reveal their impact on the relationship between data science and business employees, theorized by means of social capital. Thus, we build theoretical and practical bridges over the troubled waters in BDA collaboration and contribute to BDA success from a social perspective.

Keywords: *Big Data Analytics, Collaboration, Relational Governance, Social Capital.*

1 Introduction

In the era of big data, organisations adopt big data analytics (BDA) to support their decision-making (Sharma et al., 2014) and to improve internal processes and external offerings (Grover et al., 2018). Successfully leveraging the opportunities of BDA has the potential to differentiate between high and low organisational performance (Côrte-Real et al., 2019). However, the possibilities of BDA face several challenges, which are grounded in the data, in the related process, and in the management of BDA (Sivarajah et al., 2017), initiating massive transformation efforts within many organisations (Dremel et al., 2017). Research indicates that managerial issues even outweigh the technological issues (Wegener and Sinha, 2013), which draws attention to the human side of BDA. As one example of these managerial challenges, the troubled relationship between data science experts and business users has been introduced as one under-researched reason why BDA projects still frequently fail (Hagen and Hess, 2021; White, 2019). Besides software experts who deliver the technological infrastructure, data science experts and business users are the central collaborators in BDA, being responsible for improving organisational decision-making (Michalczyk et al., 2021). However, there is evidence that their working relationship is troubled and lacks social capital (Barbour et al., 2018; Hagen and Hess, 2021). These weak social bonds may impede collaboration for BDA. Especially in pre-digital organizations (Chanias et al., 2019), tension arises from diverse relational difficulties (e.g., incongruent mind-sets, unrealistic expectations) and change-inherent challenges (e.g., power struggles around decision-authority). This impaired collaboration holds the potential to diminish BDA project success. A similar constellation between business and IT as different professional groups has kept IS on tenterhooks for decades (Chan, 2008; Van Den Hooff and De Winter, 2011), urging information systems (IS) scholars and practitioners to look carefully at this new relationship to avoid similar mistakes.

To address the challenges associated with BDA, organisations must govern their BDA activities. BDA governance refers to "establishing and following structures, rules, policies, and controls for data analytics activities" (Gröger, 2018) and can be split into a structural, procedural, and relational dimension (Baijens et al., 2020). Governing the collaboration between business users and data scientists falls into the relational spectrum, including communication, knowledge sharing, and alignment (De Haes and Van Grembergen, 2004; Peterson, 2004). While there is a rich body of literature on (relational) IT governance, research on BDA governance is still in its infancy. Baijens et al. (2020) developed a BDA governance framework, and Fadler et al. (2021) established data governance archetypes, whereby both studies provide a broad and general overview of this topic. Few studies investigate the governance mechanisms in detail, especially the relational mechanisms. Thus, we lack a theoretical and practical understanding of how concrete collaborative mechanisms can improve the troubled working relationship. Against this backdrop, we follow Markus (2017), who argues for a more substantial consideration of stakeholders involved in big data, and Mikalef et al. (2020), who found that the human factor of BDA value has been barely researched. Against this background, we argue that to improve collaboration for BDA, the social relationship between data science experts and business users must be improved. Building on the initial work in IS, we deep-dive into the relational mechanisms in BDA and investigate which collaborative approaches organisations apply and how they foster the relationship between data science experts and business users. Two research questions (RQ) guide our study:

RQ 1: *Which collaborative mechanisms do organisations apply to foster the relationship between business users and data science experts during joint BDA projects?*

RQ 2: *How do these collaborative mechanisms influence the relationship?*

We conduct an exploratory multiple-case study with eight digital-savvy organisations to explore their collaboration design and to investigate the connection of the collaboration mechanisms with the relationship between business users and data science experts. To operationalize collaboration for BDA and its mechanisms, we build on the layer model of collaboration by Briggs et al. (2009). To assess the impact of the measures on the relationship, we apply social capital theory (Nahapiet and Ghoshal, 1998). Our study contributes to the literature on BDA governance by shedding light on relational governance mechanisms and their levers to impact the relationship. Additionally, we provide guidance especially for pre-digtal organisations that implement BDA, as we show best practices from born-digital organizations from which they can learn how to design collaboration within BDA projects. Thus, we build bridges over the troubled waters in BDA collaboration and contribute to BDA project success from a social perspective.

2 Theoretical background

2.1 Collaboration for big data analytics

"Collaboration" means that two or more individuals work jointly on an intellectual endeavour (Webster, 1992). It is a complex process that requires coordination, communication, meaning, relationships, and structure (Kotlarsky and Oshri, 2005). Groups collaborate to create value that cannot be developed individually by leveraging diverse skills (Briggs et al., 2009). Successful collaboration, in turn, is "the process through which a specific outcome, such as a product or desired performance, is achieved through group effort" (Kotlarsky and Oshri, 2005, p. 40). BDA, which is defined as "the application of statistical, processing, and analytics techniques to big data for advancing business (Grover et al., 2018, p. 390), also requires collaboration and a multitude of skills. Specifically, it necessitates business, analytical, and technical skills, which are shared efforts by business users, data science experts, and software experts (Michalczyk et al., 2021). In this work team (Carton and

Cummings, 2012), business users are managers from various business units, e.g., marketing, who aim to use BDA to improve their decision-making. Data science experts (the abbreviation 'DS' will be used in the following to ease readability) are, for example, data scientists and data engineers, who contribute their analytical and technical understanding to extract knowledge from data (Michalczyk et al., 2021). Lastly, IT specialists (e.g., software developers) are the technical enabler of BDA, providing the technological infrastructure and turning data science prototypes into applications (Vidgen et al., 2017). DS experts are the new organizational actor within this collaboration, as BDA is "not just a faddish rehashing of already existing technical competencies in organisations, but the emergence of a new function" (Barbour et al., 2018, p. 258). Thus, business managers who want to use BDA must establish new relationships with these experts. As BDA is a functional competency, not a technical competency (Avery and Cheek, 2015), we explicitly focus on these two groups of the BDA work team and understand collaboration for BDA as a joint effort of DS experts and business users during the process of BDA who aim at improving organisational decision-making. Paying tribute to the novelty of the BDA phenomenon, we allow ourselves to exclude IT specialists. Their BDA enabler role is not debatable, but they are not seen to be at the forefront of organisational decision-making and BDA management (Pearson and Wegener, 2013).

To operationalize collaboration mechanisms for BDA and to answer RQ1, we build on the layer model of collaboration by Briggs et al. (2009). This model has been developed based on more than 400 collaboration science research papers in the domains of information systems, psychology, and management, amongst others. As a synthesis of this literature, it has been created to support collaboration design in IS and helps separate conceptual matters related to collaboration. We used this framework as basis for our interview guide (section 3.1), and to cluster our results (section 4.1). By using this framework, we aim for "completeness and consistency" (Briggs et al., 2009, p. 1), and consider differing levels of abstraction. The layers are goals, products, activities, techniques, tools, scripts, and patterns. Table 1 describes these layers and provides examples from current literatur of how they are manifested in BDA.

Layer	**Description (**Briggs et al., 2009)	**Examples in the context of BDA**
Goals	Desired state or outcome of the collaboration	• Process improvement, product and service innovation, reputation (Grover et al., 2018)
Products	Tangible or intangible artefacts / outcomes produced by the work team	• Machine learning solutions to detect health risk factors (Zhang and Ram, 2020) • Deep learning models to analyse visual data in social media (Shin et al., 2020)
Activities	Sequences of steps / subtasks to achieve the goals	• CRISP-DM model (Mariscal et al., 2010) • Information value chain (Abbasi et al., 2016)
Techniques	"Reusable procedure[s] for invoking useful interactions among people working toward a group goal" **(**Briggs et al. 2009, p. 3)	• Design-thinking workshops (Hagen, 2021) • Trainings (Fadler et al., 2021) • Conferences (Baijens et al., 2020)
Tools	Artefacts used in performing an operation for moving a group toward its goals	• Online communication tools (Baijens et al., 2020) • Process tracking tools (Baijens et al., 2020)
Scripts	Everything team members say to each other (tacit or explicitly documented)	• Formalized data strategy (Hagen, 2021) • Success stories (Baijens et al., 2020)
Patterns[1]	Observable regularities of behaviour and outcome that emerge over time	• Six patterns, e.g., generate, reduce, clarify, build commitment (Briggs et al., 2009)

Table 1. Areas of concern for collaboration design in BDA (based on Briggs et al., 2009).

[1] As this area of concern in collaboration design has to be observed over time, it is excluded from our research, which is a cross-sectional study, not a longitudinal analysis.

BDA literature emphasises the need for cross-department collaboration and a good working relationship between business users and DS experts (Gupta and George, 2016). However, research has shown that this relationship is troubled. Relational challenges especially seem to appear in pre-digital organizations (Chanias et al., 2019). These organizations used to be successful prior to the era of digital transformation and do not have the same amount of data-orientation in their organizational DNA as born-digital organizations who "intensely leverage digital technologies as critical elements of their business models from their inception" (Tumbas et al., 2017, p. 2). Specifically, tension arises from direct relational difficulties and change-inherent challenges. On the one hand, the different professional backgrounds of business users and DS experts lead to different languages and incongruent mind-sets (Hagen and Hess, 2021). Moreover, there may be a lack of social skills among data scientists, who may act solely as "number crunchers" without making any effort to build bridges with business and to share their competencies (Troilo et al., 2017). Furthermore, research indicates that business users have unrealistic expectations regarding the possibilities of BDA and are not sufficiently aligned internally when it comes to the utilization of BDA solutions. Also, the organisational and structural conditions may seem insufficient, for example, regarding joint processes (Hagen and Hess, 2021). Formulated from a theoretical perspective, the relationship lacks cognitive, structural, and relational social capital (Hagen and Hess, 2021). On the other hand, tension arises from the shaken power structure and organisational hierarchy during BDA projects. BDA can be seen as a form of organisational change that breaks up existing routines and leads to insecurity due to new requirements (Collins, 2002). Here, BDA holds the potential for re-negotiating established organisational hierarchies and power relations (Pfeffer, 1992) as DS experts gain increasing importance within the organisation. In this setting, pressure arises around the question about the decision authority, for example. Thus, business users may hoard their data to maintain their influence, fearing that algorithms make their judgement obsolete (Barbour et al., 2018).

In essence, we find that scholars have paid attention to the disorders in the relationship between DS experts and business users, revealing that severe relational and hierarchical issues characterize the BDA work team. These differences hold the potential to impede the relationship and thus collaboration for BDA. Here, the question arises of how this relationship can be fostered by means of distinct collaborative mechanisms to increase success rates of BDA projects, which still fall short of expectations (White, 2019). To address this gap, an in-depth investigation of relational governance in BDA appears useful. As for the relation between business and IT, relational governance mechanisms are defined as "the active participation of, and collaborative relationships among, corporate executives, IT management, and business management" (Peterson, 2004, p. 15). Whereas IS literature has provided various solutions for business and IT (e.g., Luo et al. (2016)), literature on relational mechanisms for BDA is in its infancy. In their holistic work on analytics governance mechanisms, Baijens et al. (2020) revealed initial approaches to how organisations facilitate shared perception (e.g., via success stories), collaboration (e.g., via frequent meetings), and knowledge transfer (e.g., via online platforms). Fadler et al. (2021) revealed initial approaches for relational governance in their work on data governance archetypes, highlighting how organisations support communication (e.g., via data standards and compliance), alignment (e.g., via colocation), and knowledge sharing (e.g., via training) during BDA projects. Hagen (2021) discloses high-level approaches how to foster the relationship, showing that it necessitates joint goal definition, for example. Building on these works, we aim to dive deeper into the relational mechanisms for BDA, specifically revealing how organisations facilitate collaborative goals, products, activities, techniques, tools, and scripts. Additionally, we strive to shed light on how these mechanisms influence the relationship.

2.2 Social capital theory

Social capital is "the sum of the actual and potential resources embedded within, available through, and derived from the network of relationships" (Nahapiet and Ghoshal, 1998, p. 243). It facilitates the activities of actors within a social structure (Coleman, 1990). Nahapiet and Ghoshal (1998) distinguish three interrelated dimensions of social capital. The cognitive dimension refers to shared interpretations and systems of meaning among groups, for example, shared language, codes, and narratives. The structural dimension refers to the network of relations and the overall connection patterns between actors, for example, network ties, and identifiable pattern of linkages. The relational dimension refers to the quality of relationships between actors that influences the behaviour, for example, trust, expectations, and friendship. Scholars found that the higher the social capital within a group, i.e., the better the relationships between the members, the better its performance (Aquino and Serva, 2005). This tends to happen because the presence of social capital can reduce transaction costs, enhance mutual commitment, and facilitate collaboration (Van Den Hooff and De Winter, 2011).

Besides other fields of application (e.g., education), the social capital theory has been applied to the relationship between a business and a non-business group. Van Den Hooff and De Winter (2011) and Wagner et al. (2014), for example, found a lack of social capital between business and IT, and Hagen and Hess (2021) revealed that business and data science also lack social capital along all three dimensions, which impedes collaboration for BDA. As the presence of social capital has a positive impact on collaboration, we argue that organisations may actively design their collaborative mechanisms in a way that they positively influence the social capital between DS experts and business users. We presume that especially pre-digital organizations can benefit from that to improve their inferior collaboration setting. In this vein, we apply social capital theory to answer RQ2 and to assess how the collaborative mechansism impact the relationship. Figure 1 summarizes our research framework.

	RQ1	RQ2
Research object	**Collaborative mechanisms in BDA projects**	**Relationship between data science experts and business users**
Operationalization	Goals, products, activities, techniques, tools, scripts	Cognitive, structural, relational social capital
Foundation	Layer model of collaboration (Briggs et al. 2009)	Social capital theory (Nahapiet and Ghoshal 1998)
Purpose	Structure interview guide and results	Assess impact on relationship

Figure 1. Research framework.

3 Method

We chose an exploratory multiple-case study research design as this is well suited to examine real-life problems in depth in their natural context (Yin, 2014). Case studies are applicable in the exploratory phase of a topic and thus a suitable method as we want to explore collaborative mechanisms and their impact on the relationship. Additionally, they are well suited to answer “how” questions. To ensure empirical rigour, we adhere to the guidelines of qualitative research (Dubé and Paré, 2003).

3.1 Case selection and description

To capture best practices regarding the collaboration approaches, we selected the case organizations in a two-step approach. First, we made sure that the cases fulfil our three selection criteria:

- The organization is born-digital (Tumbas et al., 2017), and as such used to work with (big) data from its inception, or a pre-digital organization (Chanias et al., 2019) with proven innovative ways of working (e.g., agile), and sufficient (≥ five years) experience with BDA
- The organization is experienced in facilitating the collaboration of DS experts and functional managers with distinct measures
- The organization does not report significant collaboration issues

Second, we used a theoretical replication logic to select diverse cases to allow contrasting findings (Yin, 2014). We terminated case acquisition after we reached the point of theoretical saturation (Eisenhardt, 1989), that was, no new collaborative mechanisms or relationship impacts were reported. The final sample includes eight firms of various sizes from different industries and with different business models, headquartered in Europe. Hence, our sample represents a comprehensive portrait of organisations utilizing BDA and facilitating collaboration between DS and business users. The cornerstones of the collarboation for BDA at the respective organization is outlined in the following.

RetailCo is an online retailer which provides a shopping platform that focuses on personalized shopping experiences enabled by BDA. Since data is at the core of the business model, DS and business collaborate closely, however, in separate teams. RetailCo requires that business users have basic DS-skills.

PublishCo is a leading digital media publishing company that implements advanced technologies to provide personalized content. Data competencies are bundled in a DS team and a business analytics team. Additionally, business users get analytic training to excel their understanding.

CopyCo is a leading organisation for musical performing and mechanical reproduction rights, which is undergoing a wide-ranging BDA transformation. Currently, the main aim of BDA projects is the optimization of internal processes and the provision of intelligent online services. The DS team collaborates with business units, which have no or little BDA capabilities yet.

MediaCo is a media company that has a diversified digital media product portfolio (e.g., TV shows, digital media library). Two years ago, the company founded a central DS unit. Their main goal is to use advanced data analytics technologies to generate predictions about user behaviour and improve their media product offerings.

EntertainCo is a large private television provider that offers a movie and series streaming platform next to traditional television channels. The main aim of the BDA projects is to motivate customers to interact with the platform and use their products, which involves the implementation of recommender systems. DS is anchored as a central unit and collaborates case-based with the business units.

AdCo is a leading technology firm offering various online products and services. BDA is mainly used to improve internal processes. Almost all employees have sophisticated DS skills, and collaboration for BDA is well established.

AerospaceCo is a leading company for aerospace technology that manages large amounts of data. BDA is used to provide external data-driven solutions and to improve internal processes. AerospaceCo has a central DS division that provides data expertise for company-wide business cases.

SaaSCo offers B2B software as a service. The firm has a BDA department that focuses on developing data dashboards as a basis for data-driven decision-making. Each business units collaborates with this BDA department.

3.2 Data collection

Data collection took place from 06/20 to 03/21. We conducted 28 individual interviews, which were executed via video conferencing tools (see Table 2 for an overview of the cases and the interviewees). They lasted from 40 to 70 minutes and were supported by a semi-structured interview guide consisting of three parts. The introductory part included general questions about, e.g., the interviewee's role, how the organization uses BDA, and which parties are involved. The main part examined the six collaboration layers. For every layer, the interviewee was asked to describe the manifestations, to evaluate (dis-)advantages, and to assess its impact on the relationship. The last part included questions on the importance of the layers for the collaboration, and general success factors, amongst others. Also, we asked if there are any other layers or mechanisms the interviewees want to mention that were not covered before. As this question did yield no results, the collaboration model of Briggs et al. (2009) proved to be exhaustive for our application. All interviews were recorded and transcribed verbatim. To code and analyse the data, we used ATLAS.ti. In the results section, we use interviewee IDs as quotation sources. For example, "Retail1B" indicates a quote from the product owner of RetailCo. The interview data was enriched with secondary data (e.g., firm websites, management reports) to build the case descriptions and to validate the role of BDA for the organization.

Case organisation	Revenue (€) / employees (2020)	Interviewees B=business user, D=data science, BD = hybrid profile
RetailCo *(Online retailer)*	~ €170 *Mn.* / 965	1) product owner (B), 2) data scientist (D), 3) data engineer (D), 4) data analyst (BD)
PublishCo *(Online media publisher)*	*~ €115 Mn. / 800*	1) product owner (B), 2) head of data science (D), 3) data scientist (D), 4) chief information officer (BD)
CopyCo *(Copyright collecting)*	*~ €860 Mn. / 1,070*	1) data strategy developer (B), 2) head of data science (D), 3) data scientist (D), 4) chief information officer (BD)
MediaCo *(Media and entertainment)*	*~ €3,5 Bn. / 7,000*	1) data product manager (B), 2) data strategist (B), 3) data scientist (D)
EntertainCo *(Media and entertainment)*	*~ €16 Bn. / 32,000*	1) data architect (D), 2) business intelligence architect (D), 3) director advanced analytics (BD)
AdCo *(Advertising)*	*~ €155 Bn. / 135,000*	1) sales leader (BD), 2) associate account strategist (BD), 3) account strategist (BD)
AerospaceCo *(Aerospace technology)*	*~ €9.5 Bn. / 40,000*	1) product management officer (B), 2) data scientist (D), 3) data scientist (D), 4) head of data science (BD)
SaaSCo *(Data privacy software)*	*~ €6 Mn. / 100*	1) head of finance (B), 2) data architect (D), 3) data analyst (BD)

Table 2. Cases and conducted interviews.

3.3 Data analysis

We performed three cycles of coding (Miles et al., 2014). First, to answer RQ 1, we inductively assigned descriptive codes to the data to summarize the basic topic of the phrases. This yielded the collaborative mechanisms. Second, we deductively clustered the mechanisms. Therefore, we used the description of the collaboration layers of Briggs et al. (2009) as basis. To answer RQ 2, the clustered collaborative mechanisms were deductively assigned to the social capital dimensions in a third coding cycle, using the descriptions provided by Nahapiet and Ghoshal (1998). Therefore, we took the identified quotes regarding the expressed advantages of the respective mechanisms, and matched them with either relational, cognitive, or structural capital. To ensure stability and inter-coder reliability, two researchers did the coding procedure individually (Krippendorff, 2013). In unclear cases, fellow researchers joined the discussion. Table 3 provides examples of the applied coding scheme.

Quote	**Collaborative mechanism** 1st cycle, inductive	**Collaboration layer** 2nd cycle, deductive (Briggs et al. (2009)	**Social capital dimension** 3rd cycle deductive (Nahapiet and Ghoshal (1998)
"If you have *developed a common goal*, then a group <u>feels like one unit</u>." (Media1B)	*Goals derived in joint dialogue*	Goals	<u>Relational</u>
"Business *defines what they expect and what they need*, and the data analysts define what can be expected and then both have a <u>common understanding</u>." (Aerospace1B)	*Definition of requirements / use cases*	Activities	<u>Cognitive</u>

Table 3. Coding examples.

4 Results

We present the results of our study in two steps, adhering to our two RQ. First, we present the collaborative mechanisms applied by the companies, sorted according to the layers of the collaboration model (4.1). Second, we reveal the levers by which the identified collaborative mechanisms impact the three social capital dimensions (4.3).

4.1 Collaborative mechanisms

Goals: All case organisations attach importance to a joint goal development, either in a less formalized *dialogue* or embedded in *OKR* (objective key results), an agile management approach. In any case, overarching goals serve as a point of reference for business and DS. At PublishCo, for example, the company vision serves as an overarching goal for both groups, and specific collaboration goals evolve from business hypotheses for data products. CopyCo differentiates implicit and specific goals. Implicit goals are rather broadly formulated and reflect general interests or pain points. Specific goals are measurably formulated, and metrics to reach the goal are defined collaboratively. At MediaCo, the high-level joint goal is the mission to constantly improve data products, wherefrom specific joint goals are derived in a dialog. At RetailCo, the management board sets the high-level goals quarterly via OKR. Afterwards, each department derives its respective sub-goals. In an OKR workshop, DS and business align the common sub-goal. "It needs some time to achieve the alignment. You just come from different directions." (Retail4BD). At AdCo, OKR workshops are utilized to rank company projects assigned to respective goals according to their importance. At SaaSCo, both groups collaborate and share the same goal whenever a collaboration helps the business units to reach their OKRs. Across all cases, both groups usually play an equal role in goal setting. One exception is AerospaceCo, where DS decides independently whether a goal is pursued. Aerospace4BD explains: "Once we start working on a project, it was because there was filtering from our side of meaningful projects that are reusable for other units. By the time the project lands on our list, we share the goal."

Products: The case organisations collaborate for BDA either to develop *internal dashboards for decision-making*, or *data products that automate internal manual processes*, or to *improve external customer services*. Prediction models to forecast customer behaviour are developed in several cases, representing an example for internal-oriented BDA products. Recommender systems represent a frequently developed external BDA solution. In all cases, both groups are equally responsible for product development. "Otherwise, if something goes wrong, then it is always the others who are to blame, and this is why we have managed it together" (SaaS2D).

Activities: All collaborations are initiated based on concrete *business needs*, which are, in most cases, identified by the business users. At EntertainCo, the use case detection is also supported by the data unit that provides data reports. Exceptionally, at AdCo, a dedicated product leader interacts with both groups to collect ideas for new BDA solutions. At EntertainCo, DS can also actively introduce ideas for specific data use cases to provide business value. The business need, often represented in *use cases*, is then translated into *requirements*. Here, business users are in the driver's seat but often receive support from DS. "We encourage business that they need to spend time with us to give us enough business context, answer all our questions, as we jointly own the accountability for the solution" (Aerospace2D). Next, the use cases and requirements are checked by DS regarding their *technical feasibility*. Then, in some cases, the business value is estimated precisely based on the information available, primarily by business users. Subsequently, both groups define the tasks for the project implementation, and diverse approaches are used to synchronize tasks throughout the project (see techniques below).

Techniques: Most of the case organisations utilize *Scrum* as a joint agile project management technique. CopyCo highlights the importance of feedback and therefore values Scrum, where regular meetings enable to reflect project progress and foster interaction. Besides, scheduled priorities help to focus on current tasks. However, Entertain1D underlines that "the concrete problems must be kept in mind and should not be subordinated to agile working." In this vein, all organisations execute additional *situation- and needs-oriented meetings* next to Scrum. CopyCo, for example, schedules a meeting for DS and business every six weeks where new technologies are introduced and brainstorming sessions for potential BDA use cases are executed. Another technique for invoking useful interactions between business and DS is the use of *intermediaries*. At RetailCo and CopyCo, for example, the intermediary is a data analyst who has DS skills, but is physically available for the business users, which enables them to quickly access data and send ad-hoc requests to DS. The intermediary is involved in meetings of both teams. MediaCo even engages a whole intermediary team. Moreover, *prototypes and minimum viable products* (MVP) help to align the groups. They provide transparency and visibility in an early development phase, and business users can give feedback before the product is fully developed. Additionally, it ensures that product requirements are implemented as imagined. To increase company-wide data skills, PublishCo and AerospaceCo offer *DS training* for business employees. AerospaceCo even gives the opportunity to obtain a Nano degree in data analytics, which is provided by a university and paid by the company. To date, 1,200 business employees completed this degree. Another collaborative technique is the use of *success stories*, which specifically fosters the future implementation of BDA projects. AerospaceCo executes internal events, where successful BDA collaborations are demonstrated: "There you get a little summary of the collaboration and see the value of our work. So, the outcome of the collaboration leads to more potential requests in the future because we can prove value". (Aerospace4BD). Besides the standardized Scrum feedback, CopyCo deploys *inter-group feedback sessions* on a personal level. They are part of the yearly team building meeting and essential since "the real professional and technical problems of a project account for 20 percent and 80 percent are interpersonal" (Copy4BD).

Tools: All case organisations apply digital tools from diverse providers to facilitate collaboration, i.e., *communication and project management tools*, *ticketing systems*, and *version control systems*. For example, RetailCo uses a ticketing system for task management enabling an efficient and objective prioritization. Further, RetailCo works with version control systems allowing business and DS to work on the same file and track edits. At PublishCo, DS and business can upload project ideas as a ticket to a "service desk." AdCo uses internally developed tools to support collaboration, e.g., video conferencing, ticket tools, or chat. As AdCo capitalizes on personal feedback, DS and business can send feedback forms via an integrated ticketing tool to persons from whom they would like to request feedback. Lastly, MediaCo uses a workshop tool, which enables to execute virtual workshops.

Scripts: The scripts used most frequently during the collaboration for BDA are *project documentations* in various forms. For example, RetailCo values comprehensive project descriptions that illustrate the progress of the project. Every project member can access these scripts in a collaboration tool and document task accomplishments or difficulties. At PublishCo, business and DS experts jointly set up a project documentation when starting a BDA project. The document outlines the hypothesis and business value of the project and evolves throughout the project. Although CopyCo works agile, it documents the required achievements of projects in a project report. This ensures that project information is consolidated and enables continuous information access. Moreover, CopyCo uses an *information map* that shows which departments generate what kind of data. Thus, DS and business experts can find the right contact persons for specific data questions. Besides other widespread project management documents such as *decision and tasks protocols*, a *BDA process organigram* is used, which displays responsibilities for tasks of a BDA process (EntertainCo). Table 4 summarizes the applied collaborative mechanisms and their distribution across the case organisations.

Collaboration layer	Collaborative mechanism	RetailCo	PublishCo	CopyCo	MediaCo	EntertainCo	AdCo	AerospaceCo	SaaSCo
Goals	• Goals derived in a joint dialogue		x	x	x	x		x	
	• Goals derived formalised via OKR	x					x		x
Products	• Internal (dashboards, process automation)	x	x	x	x	x	x	x	x
	• External (customer products and services)		x	x	x	x		x	
Activities	• Project initiation based on business need	x	x	x	x	x	x	x	x
	• Definition of requirements / use cases	x	x	x	x	x	x	x	x
	• Check of technical feasibility	x	x	x	x	x	x	x	x
	• Proof of business value		x			x	x	x	
Techniques	• Needs-oriented exchange meetings	x	x	x	x	x	x	x	x
	• Scrum	x	x	x	x	x		x	x
	• Intermediaries	x		x	x				
	• Prototyping / MVP			x	x				x
	• Data analytics training / degrees		x					x	
	• Success stories			x				x	
	• Personal inter-group feedbacks			x					
Tools	• Project management / communication tools	x	x	x	x	x	x	x	x
	• Ticketing systems	x	x		x		x		x
	• Version control systems	x	x	x	x				
Scripts	• Project documentations	x	x	x				x	x
	• Decision and / or task protocols				x	x			
	• Information map (prevalent data per unit)			x					
	• BDA process organigram					x			

Table 4. Collaborative mechanisms for BDA projects.

4.2 Impact of collaborative mechanisms on the relationship

We now present the identified connections between the collaboration layers and the social capital dimensions. Also, we outline the specific levers by which the collaboration mechanisms influence the relationship. Based on the interviews, we find that five of six layers, i.e., goal, products, activities, techniques, and tools, contribute to all three social capital dimensions, i.e., cognitive, structural, and relational. The scripts layer is an exception and only contributes to cognitive capital. The figures following every subsection illustrate the connections of the mechanisms, and their respective levers.

Cognitive social capital: Based on 62 of 123 codes across all cases, we find a strong connection of all collaborative mechanisms with cognitive social capital. Half of the cases report that *goals* influence cognitive capital, for example, by facilitating the derivation of subsequent joint approaches. Three cases connect *products* to cognitive capital. Products can be seen as a reflection of mutual understanding: "The better the common understanding of the product, the higher the chances of success in the end" (Publish2D). *Activities* are mentioned by six cases to have a positive impact, as joint activities "create a mutual understanding of feasibility and requirements" (Copy2D). All cases report that *techniques* also facilitate the development of mutual understanding. Offering BDA training for business users, for example, makes knowledge accessible. "This way, a common basis can be developed which is necessary to be able to solve problems together. I have equipped colleagues with a basic understanding of machine learning" (Publish2D). Seven cases emphasize that *tools* help provide information, which fosters mutual understanding. "You can share information and work very efficiently" (Copy2D). Also, "less knowledge gets lost" (Media3D). This yields that "everybody is up to date, you know what everybody is working on and what problems the other one has, and maybe you have a solution for it" (SaaS3BD). Six cases report that *scripts* also contribute to cognitive capital, as they "support the transfer of information and the overall understanding" (Media2B). Media3D states: "These scripts force that everyone has the same understanding", and Ad3BD supports: "documentation is essential, because otherwise, you have a huge loss of knowledge".

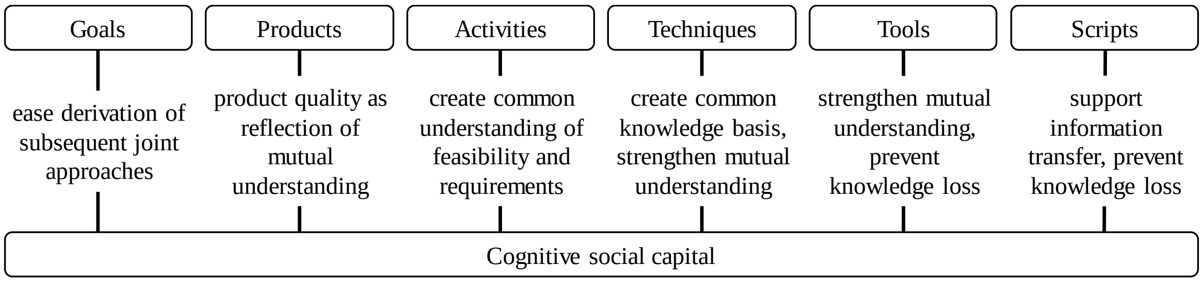

Figure 2: Collaboration layers and their levers to impact cognitive social capital.

Structural social capital: 33 codes of 123 codes across all cases were assigned to the structural dimension. Four cases highlight the influence of the *goal* layer. The interviewees accentuate that joint goals lead to more interactions between DS and business strengthening the network. Due to common goals, "you feel more connected to the other people" (Ad2BD). Through the closeness to each other, DS and business create a close network: "You build a network, so I know who to turn to if I want to know something about special topics" (Copy1B). Two cases report that *products* contribute to structural capital by uniting DS and business like "a welding element" (Publish4BD). Six cases explain that meshed *activities* increase interaction frequency and thus facilitate network creation and the development of network ties. "Working together is intensified and takes place repeatedly" (Ad2BD). Through meshed activities, "you are not afraid of simply writing to a person directly, because you have this frequency of interaction, which leads to more open communication" (Ad1BD). Four cases describe that *techniques* contribute to the structural capital by connecting the groups and thus building a network: "Through such mechanisms, I can strengthen the connection to the team" (Ad2BD). Three cases report that *tools* act as a facilitator for connecting DS and business: "Digital collaboration tools are a key element that makes it much easier to work together" (Publish2D). Moreover, tools illustrate responsibilities that give a clear overview of the network. "Having assigned responsibilities makes it clear to everyone who has to do what, by when, why and what the next steps are. This gives the whole thing structure." (Ad3BD). Entertain1D explains: "If the data scientists have a question, they know through which channels they can contact us quickly." No interviewees address that scripts have a connection with structural capital.

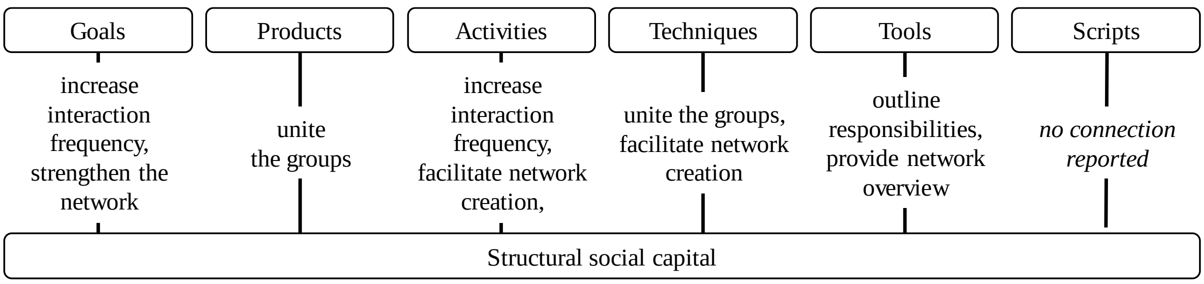

Figure 3: Collaboration layers and their levers to impact structural social capital.

Relational social capital: The connection of the collaborative mechanisms with relational capital is reflected in 28 out of 123 codes across all cases. Seven organisations mention the contribution of *goals*. Joint goals foster that both groups appreciate each other since mutual commitment is necessary to reach joint goals: "You meet at eye level, you appreciate each other. Without business we don't have a job, and they don't have the numbers.” (SaaS3BD). This also leads to engagement and motivation to support each other: “Everybody has a motivation with that; if you know that you have a need and the other person can solve it, and the person in front of you wants to share it with you, then it’s a joint goal.” (Aerospace2D). Four cases note that *products* influence the relational capital as the visibility of a product enables DS and business to reflect the value of their work: “If both sides see that you’re getting closer, then people see a value in collaborating” (Aerospace2D). Four cases also report that the development of a product leads to happiness: “It has a positive effect when people are happy that they have achieved something” (Media1B). Seven cases report that *activities* are also linked to relational capital. Here, joint activities between DS and business enable that both groups trust each other. “This simply promotes trust, and through trust, the partnership grows.” (Ad1BD). Furthermore, activities allow the development of interpersonal relationships. “You just get to know each other personally. That provides quality for the collaboration that you cannot measure.” (Retail2D). Lastly, the personal exchange after meetings “strengthens the sense of belonging and the interpersonal relationship” (Ad2BD). Two cases outline that *techniques* provide reliability by implementing routines. “Routines have the important task of bringing reliability and continuity into the cooperation, and structure” (Publish4BD). Two cases address that *tools* contribute to relational capital by providing reliability, e.g., “reliability that information has been stored and is made retrievable” (Publish4BD). Also, tools provide a trustful and fair environment: “It is a certain kind of fairness because it is open to everyone.” (Publish1B). This environment is also essential to enable communication. As some people may not feel comfortable speaking in front of others, they can communicate through virtual tools that “give the confidence to provide input” (Ad2BD). No cases reported an effect of scripts here.

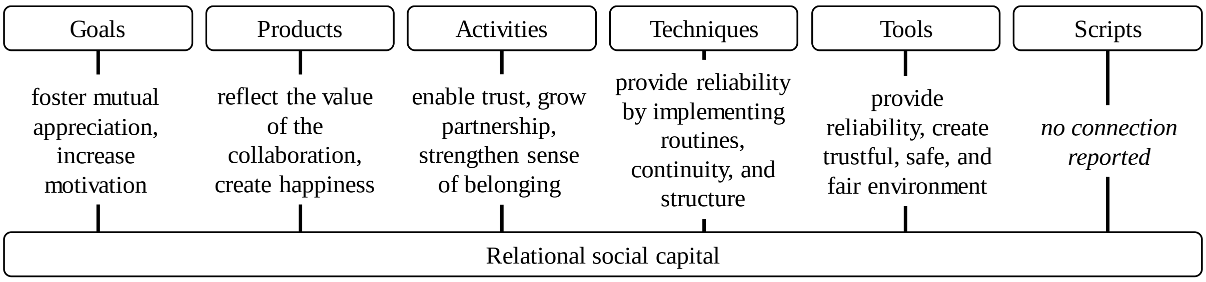

Figure 4: Collaboration layers and their levers to impact relational social capital.

5 Conclusion, contribution and further research

Our research provides in-depth insights into collaborative mechanisms and their levers to foster the relationship between DS experts and business users during BDA projects. In answering our RQ 1 *“Which collaborative mechanisms do organisations apply to foster the relationship between business users and data science experts during joint BDA projects?”* we find that all examined collaboration layers are related to the social capital between the groups. Thus, the lack of social capital between DS experts and business users can be compensated by means of distinct collaborative mechanisms. Precisely, jointly developed goals, meshed activities, reusable techniques, and collaboration tools have a high potential to improve social capital along all dimensions. In answering RQ 2 *“How do these collaborative mechanisms influence the relationship?”* we conclude:

- *Joint goals* ease the derivation of subsequent joint approaches (cognitive capital), increase the interaction frequency and thus strengthen the network ties (structural capital), and foster mutual appreciation and commitment (relational capital).
- *Meshed activities* help develop a shared understanding about the feasibility and requirements of BDA solutions (cognitive capital), facilitate network creation between the groups (structural capital), and enable trust as well as a sense of belonging to a BDA work team (relational capital).

- *Reusable techniques* (e.g., agile project management) create a shared knowledge base (cognitive capital), facilitate network building (structural capital), and strengthen trust as well as a sense of belonging (relational capital).
- *Collaboration tools* (e.g., ticketing systems) prevent knowledge loss (cognitive capital), outline responsibilities, and thus visualise the network (structural capital), and provide a trustful, fair, and safe environment (relational capital).
- *Visible products* represent the outcome of the collaboration and can be seen as a reflection of the mutual understanding prevalent during the collaboration (cognitive capital). Moreover, common products bond the groups (structural capital) and are a pars pro toto for the value of the collaboration (relational capital).
- *Explicitly documented scripts* (e.g., shared documentations of business hypotheses and value connected to the BDA solution) are crucial to strengthening cognitive capital. They foster a mutual understanding and prevent knowledge loss (cognitive capital).

With our findings, we contribute to theory and practice alike. From an academic perspective, we address related calls for a stronger consideration of human aspects during BDA (Markus, 2017; Mikalef et al., 2020) by unveiling solutions how to foster the troubled relationship and collaboration between business users and DS experts. Specifically, we progress recent research on (relational) governance mechanisms in BDA (Baijens et al., 2020; Fadler et al., 2021) by zooming into a multitude of collaborative mechanisms along various layers. Thus, we also respond to Avery and Cheek (2015) who state that human capital development is an important aspect of BDA governance. From a theoretical perspective, we pick up on research that underlines the lack of social capital between business users and DS experts and show how this social capital can be strengthened. By doing so, we go beyond the descriptive compilations of governance mechanisms and enrich recent BDA governance research by shedding light on the effects of relational governance mechanisms in BDA. Specifically, it has been found that business users and DS experts lack social capital along all three dimensions, first, cognitive and structural social capital, followed by relational capital (Hagen and Hess, 2021). To diminish the gap in cognitive capital, we propose, for example, to use shared documentations of business hypotheses and value connected to the BDA solutions, as they foster a mutual understanding and prevent knowledge loss. To diminish the gap in structural capital, we propose, for example, focusing on meshed activities as they facilitate network creation and the development of network ties. Moreover, we add to BDA literature that emphasises the need for cross-department collaboration and a good working relationship during BDA projects (Gupta and George, 2016), but to date missed out on providing concrete solutions of what this can look like in terms of distinctive collaboration activities. Our study is also relevant for executives entrusted with BDA, managers responsible for data-driven operations, and employees in charge of change management and human resources, especially in pre-digital organizations. Practitioners may understand our study as a tool kit that guides them in defining targeted approaches for relational BDA governance, learning from born-digital organizations. Given limited resources, execution priorities can be set according to the most troubled dimension(s) of social capital in the respective organisations. Moreover, transparent structures and joint approaches may calm shaken power structures as they explicitly allocate decisions rights.

Our study does not come without limitations that open research avenues for this infant field. First, our results should be seen as initial explorative work based on qualitative data. Our assumed connections between collaborative mechanisms and social capital are not based on statistical evaluations but derived from the cases. Quantitative studies that validate our findings are necessary. Second, we have explored digital-savvy organizations, as we were interested in successful collaborations. Investigating pre-digital organizations that suffer from inferior collaboration settings may be fruitful to explore possible frontiers of the mechanisms. Third, other BDA stakeholders (i.e., IT specialists) have not been considered. Fourth, our research does not connect our findings to specific organisational circumstances, e.g., the organisational anchorage of the teams (i.e., central, decentral, hybrid). Further investigations of these dependencies may be valuable to derive even more targeted recommendations. Lastly, we encourage further research on structural and procedural BDA governance mechanisms and how they influence relevant outcome variables to advance the field of BDA governance.

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