Understanding interorganizational big data technologies: How technology adoption motivations and technology design shape collaborative dynamics

Katharina Cepa
Lancaster University Management School

ABSTRACT  Organizations increasingly employ big data technologies to capture, represent, and analyse complex operational processes at the organizational interface. This provides opportunities to learn about and optimize collaboration processes, which should increase cooperation. Yet, organizations may not learn equally, which could trigger learning races and thereby foster competitive dynamics. This multiple case study of 13 interorganizational relationships reveals four paths that explain how organizations’ technology adoption motivations and different technology designs conjoin to shape collaborative dynamics: where organizations pursue complementary motivations of learning and efficiency, collaborative dynamics are cooperative (path 1). Where organizations pursue shared learning motivations, interaction dynamics are cooperative if big data technologies provide shared analytical processing capability and symmetric transparency (path 2) or competitive where big data technologies provide shared analytical processing capability and asymmetric transparency (path 3) or non-shared analytical processing capability regardless of transparency (a)symmetry (path 4). These findings advance strategic management literature by showing that big data technologies accelerate interorganizational learning, but that collaborative dynamics depend on organizations’ technology adoption motivations. I also advance learning race theory by introducing transparency as extension to learning races in digital environments.

Keywords: digital technologies, interorganizational relationships, learning races, transparency

INTRODUCTION

The recent proliferation of big data technologies in organizations transforms work practices (Curchod et al., forthcoming; Jonsson et al., 2018; Leonardi, 2007; Orlikowski and
Interorganizational big data technologies shape the extent and patterns of information and knowledge exchange, which may affect collaborative dynamics. Specifically, two design characteristics are pertinent. First, big data technologies allow the growing ‘data-fication’ (Lycett, 2013) of (inter)organizational processes for optimization and innovation (Günther et al., 2017; van Rijmenam et al., forthcoming). Such digital mediation of interorganizational activities creates a type of digital transparency that renders relationships and interactions knowable and evaluable (Lycett, 2013; Mayer-Schönberger and Cukier, 2014; Zuboff, 1988), helping organizations overcome limitations to information collection and exchange. Second, such greater transparency may yield faster and more effective analytical processing of the collected and exchanged data. Organizations can use this new digital transparency to create representations of complex organizational realities (Jonsson et al., 2018) that allow faster data processing and drive interorganizational learning (Larsson et al., 1998; Schildt, 2017).

A second factor shaping collaborative dynamics are both organizations’ technology adoption motivations. Interorganizational learning is shaped by both, information and knowledge exchange patterns and partners’ motivation and ability to learn and their willingness to enable inter-partner learning (Larsson et al., 1998). Where partners pursue learning motivations, asymmetric learning may render collaborative dynamics competitive (Hamel, 1991; Khanna et al., 1998).

Thus, by increasing digital transparency and augmenting analytical processing capabilities, interorganizational big data technologies may support better coordination and more, faster interorganizational learning, which likely triggers cooperative dynamics. However, where such learning is asymmetric, collaborative dynamics likely turn competitive (Hamel, 1991). Given the recent proliferation of interorganizational big data technologies, understanding how exactly their implementation affects collaborative dynamics is of great empirical and theoretical importance. Cooperative and competitive relationships provide different opportunities and require distinct governance mechanisms (Das...
I, therefore, ask the research question ‘how and why do firms’ motivations for technology adoption and big data technology designs affect collaborative dynamics?’.

My comparative multiple case study of 13 long-term interorganizational relationships shows that firms’ motivations for technology adoption and technology design conjoin to explain cooperative or competitive interaction dynamics. My findings reveal four distinct paths that explain when the introduction of big data technologies supports cooperative or competitive dynamics. These findings contribute to strategic management literature by increasing our understanding of how big data technologies affect the management of vertical alliances and by integrating symmetric transparency as new determinant for interorganizational learning races in digitally enhanced environments.

BIG DATA TECHNOLOGIES AND COLLABORATIVE DYNAMICS

Interorganizational relationships are ‘relatively enduring transactions, flows, and linkages that occur among and between an organization and one or more organizations in its environment’ (Oliver, 1990, p. 241). A relationship can be close and cooperative or more distant and competitive (Uzzi, 1997). Arising from competing interests, relationship history, and conflicting values, dynamics of collaboration are shaped by interorganizational practices of information exchange and coordination. Prior research suggests that organizations benefit from balancing cooperative and competitive dynamics (Lado et al., 1997; Stadtler and Van Wassenhove, 2016), yet, the balance tends to tip one direction or the other (Doz, 1996; Sytch and Tatarynowicz, 2014). Thus, organizations maintain portfolios of cooperative and competitive collaborations (Uzzi, 1997), while mainly adopting a single strategy for each collaboration (Hannah and Eisenhardt, 2018). This orientation towards cooperative or competitive interaction dynamics in a collaboration can change over time (Lavie et al., 2011), but is still rather stable in the short- to medium-term (Sytch and Tatarynowicz, 2014; Uzzi, 1997). Managers often see cooperative relationships as the most valuable (Kale et al., 2000).

The relative degree of cooperation and competition in an interorganizational relationship depends on the practices that connect the organizations, many of which are digitally mediated (Malhotra et al., 2007). Interorganizational information technologies increase organizations’ ability to coordinate and control partners in collaborations (Im and Rai, 2013), with an impact on relationship dynamics (Argyres, 1999; Gal et al., 2014; Li et al., 2017) and relationship roles (Jonsson et al., 2009; Lee and Berente, 2012). It is thus likely that a new wave of technology, the introduction of interorganizational big data technologies, will change collaborative dynamics (Zammuto et al., 2007).

Big data technology often serves as umbrella term to capture a range of digital technologies and applications (Lanzolla et al., 2020). These include data, different advanced analytics methods, as well as organizational knowledge and practices to apply methods to analyse big data (Baum and Haveman, 2020; Simsek et al., 2019). This rather loose definition in the management literature is understandable given their empirical novelty, but hinders the development of theorizing big data technologies and their effect on management practice. I define big data technologies here by their ability to capture, exchange, and process complex, often previously unobservable data (Lee, 2017; Rogers,
Two characteristics of such technologies on collaboration are particularly relevant for collaborative dynamics: their ability to collect and share data in an effort to create digital transparency and to process these data in an effort to generate accelerated inter-organizational learning.

**Big Data Technologies Create Digital Transparency and Improve Data Processing**

Interorganizational big data technologies can increase and formalize information and knowledge exchange. Big data technologies capture, exchange, and analyse digital real-time data of high volume, velocity, and variety (Chen et al., 2012; Jin et al., 2015; Lee, 2017). Much of ‘big data’ is created by sensors that chronicle digitally mediated production (Jonsson et al., 2018; Zuboff, 1988) and consumption (Mayer-Schönberger and Cukier, 2014; Stephens-Davidowitz, 2017; Zuboff, 2019) as it occurs. Using digital traces (Lazer and Radford, 2017) created in digitally mediated production and consumption, organizations can visualize complex products, services, and processes to create computer-augmented transparency (Schildt, 2017). This digital transparency provides new insights into products, services, and processes – insights of high granularity and timeliness with a potential to respond to observed issues immediately and from a distance (Jonsson et al., 2018).

Deploying big data technologies at the interface of collaborating organizations can create unprecedented levels of digital transparency between them. Interorganizational big data technologies ‘datafy’ (Lycett, 2013) digitally mediated operations. Information that was previously only captured as tacit knowledge (Polyani, 1958) is now systemically codified in real-time into easily transferable and analysable explicit information. This allows one organization to more precisely communicate its operational needs to their partners so they can jointly engage in optimizing processes (Boland et al., 2007; Jonsson et al., 2009; Zammuto et al., 2007). The real-time exchange and partly automated analysis of complex digital trace data in big data technologies can assist managers and employees to process more accessible and inclusive set of shared information faster (Günther et al., 2017; van Rijmenam et al., forthcoming; Zeng and Glaister, 2018).

**Determinants and Outcomes of Interorganizational Learning**

Alliance learning is shaped by the learning strategies each partner adopts. Organizations set goals regarding their own learning and expectations concerning the transfer of their knowledge to the partner (Lavie, 2006) that influence organizations’ receptivity and transparency, respectively (Larsson et al., 1998). Larsson et al. (1998) describe learning strategies as a continuum from cooperative strategies involving high receptivity and high transparency to avoidance strategies involving low receptivity and low transparency. When one partner adopts the avoidance strategy, little learning is likely to occur for either partner. When collaborating organizations both adopt a cooperative learning strategy, they are both likely to learn from each other and to generate new knowledge. Thus, one organization’s access to learning is limited or enhanced by their partner’s learning strategy (Cheung et al., 2011; Khanna et al., 1998; Larsson et al., 1998). Receptivity and transparency are often perceived to be embedded in interpersonal interactions (Hamel,
1991; Kale et al., 2000; Larsson et al., 1998). Yet, they can also be formalized in interorganizational routines and, relevant to the study at hand, in technological systems.

Differences in partner learning can trigger learning races: situations where each organization tries to learn more and faster than their partner. Having internalized the desired knowledge from an alliance, the learning race winner benefits from improved bargaining power and greater value extraction from partner inputs, which often destabilizes and risks ending the alliance. Thus, in escalating learning races, managers may choose to share fewer insights with their partners to maintain balance (Hamel, 1991). Where learning races occur, interaction dynamics are often competitive. Research shows that ‘outlearning’ partners is associated with increased stock market performance (Yang et al., 2015) and creates competitive advantage (Lavie, 2006). In a study of the US biopharmaceutical and computing industries Yang et al. (2015) found that in non-equity alliances the relatively faster learning partner achieved abnormal stock returns. This indicates that the market rewards learning race winners despite admittedly competitive effects on collaborative dynamics.

In sum, prior literature suggests that the data collection and processing qualities of big data technologies likely increase collaborating organizations’ ability to learn from and with each other (Larsson et al., 1998). Such greater interorganizational learning should foster cooperative interaction dynamics (Cheung et al., 2011; Dyer and Singh, 1998; Lavie, 2006). At the same time, learning race theory suggests that where organizations do not learn equally, interaction dynamics are likely competitive as collaborations become unstable (Hamel, 1991; Khanna et al., 1998). Which one of these two effects is stronger, and how do learning motivations and different technology designs shape these effects? With an increasing number of organizations implementing interorganizational big data technologies, this is an important question. I, therefore, explore how firms’ motivations for technology adoption and interorganizational big data technology designs affect collaborative dynamics.

**METHODS AND DATA**

To answer this question, I adopt an abductive multiple case study of 13 interorganizational relationships, each of which has introduced a big data technology to optimize specific well-defined (inter)organizational processes. Analysing such digitally enhanced vertical alliances, I aim to expand our understanding of known strategic management theories in digitally enhanced environments (Lanzolla et al., 2020).

**Empirical Setting**

I analyse the introduction of two types of big data technologies called ‘predictive maintenance’ or ‘efficiency consulting’ in long-term buyer-supplier relationships in the Northern European industrial services and manufacturing sector. In both variants, one of the two partner organizations collect sensor data, which are produced by equipment in use, transfer these data to an off-site analysis centre, analyse these data, and push back results to the other partner. Based on these analyses, one or both of the two organizations adjust operations. In cases where analyses bring adjustments to equipment maintenance
to reduce downtime or maintenance costs this is called ‘predictive maintenance’ and where adjustments pertain to the mode of equipment operations (e.g., at which capacity to operate the equipment to optimize the fuel consumption-output ratio or to reduce long-term maintenance needs) I call this ‘efficiency consulting’. The technology is similar across the cases; while relationships may use different operating systems to facilitate the processes, the reason for installation (i.e., efficiency improvement) and the technology’s functionality (i.e., provide transparency and actionable guidance on equipment use) are the same. Each technology provides coordination and learning benefits to one or both organizations. While data could be used for many other purposes from physical equipment development to selling anonymized data or analytics products, I only study these two uses here.

**Case Relationships and Their Selection**

My unit of analysis is the individual, dyadic industrial buyer-supplier relationship. I have selected case relationships based on whether they show cooperative or competitive interaction dynamics: following the introduction of interorganizational big data technologies, half my case relationships demonstrate cooperative interaction dynamics and the other half competitive interaction dynamics. I chose focal companies that were prominent in their industry or that spoke openly about their digitalization efforts in the media. Considering the novelty of the technologies, I selected companies that are leading in their industry and that communicate about their efforts to further develop them. The chosen case relationships also need to involve the purchase and/or use of a piece of heavy industrial equipment in the production of industrial services or products. This equipment needs to create sensor data which are used for equipment optimization internally in one organization or interorganizationally as part of a continuing service agreement between organizations falling under the categories ‘predictive maintenance’ or ‘efficiency consulting’.

My main source of data are interviews, supported by corporate communications and videos describing the technologies and their applications. I collected 47 semi-structured interviews (25 to 130 minutes each) in seven organizations, five focal organizations and two additional partner organizations. My interview questions focused on identifying a suitable big data technology as deployed in a given relationship, its functionality and the interactions with the partner organization surrounding its use. Additionally, I asked about general relationship descriptions and appraisals, and how technology use might have changed any aspect of the relationship. My initial entry point were Chief Executive Officers, Chief Digital Officers, or other personnel in charge of digitalization. I discussed 13 different relationships with my respondents, at times multiple customer or supplier relationships in the same interview and for the same organization. For each case relationship, I have insights from one focal company, with triangulation from their partner organization where possible. One focal company can act as buyer in one relationship, and supplier in another relationship. Please see Table I for an overview of the cases and data.

These technologies are highly strategic investments for both customer and supplier organizations, which made data collection a delicate issue. I started collecting data in one focal organization for a given relationship and then deployed snowball sampling to
Table I. Description of case relationships and interview data

| Case relationship | Supplier | Focal side | Interviews with supplier | Interviews with customer | Customer |
|-------------------|----------|------------|--------------------------|--------------------------|----------|
| Company 1         | K        | BU1: Provider of industrial services | 2 | 0 | Customer 1: Industrial production |
|                   | J        | Supplier 1: Industrial IoT services | 0 | 5 | BU1: Provider of industrial services |
|                   | L        | Supplier 2: Industrial equipment and related IoT services | 1 | 5 | BU2: Provider of industrial services |
|                   | M        | Supplier 3: Industrial services | 0 | 5 | BU3: Provider of industrial services |
| Company 2         | A        | Provider of industrial services | 2 | 0 | Customer 1: Industrial services |
|                   | I        | Supplier 1: Industrial equipment | 0 | 1 | Provider of industrial services |
|                   | F        | Supplier 2: Industrial equipment | 1 | 1 | Provider of industrial services |
| Company 3         | G        | Provider of industrial equipment and related IoT services | 8 | 0 | Customer 1: Equipment and related IoT services |
| Company 4         | D        | Provider of Industrial IoT services | 2 | 0 | Customer 1: Industrial IoT services |
|                   | B        | Provider of Industrial IoT services | 3 | 1 | Customer 2: Industrial IoT services |
|                   | C        | Provider of Industrial IoT services | 3 | 0 | Customer 3: Industrial IoT services |
| Company 5         | H        | Producer of industrial equipment and related IoT services | 4 | 0 | Customer 1: Equipment and related IoT services |
|                   | E        | Provider of industrial equipment and related IoT services | 3 | 0 | Customer 2: Equipment and related IoT services |

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*Industrial services: Use of industrial equipment to provide services to customers.
**Industrial production: Use of industrial equipment and IoT services in production processes.
***Industrial equipment: Sale of industrial equipment.
****Industrial IoT services: Use of equipment generated data to provide IoT-based service.
collect more interviews. Once I had established a relationship with a focal organization, I tried triangulating my data by collecting data also from the counter-part. However, given the high strategic importance of these technologies, this was not often successful. To mitigate this one-sided perspective, I included an even count of supplier and customer focal company perspectives across my case relationships.

**Data Analysis**

My data analysis proceeded abductively, following guidelines for comparative multiple case studies (Eisenhardt, 1989; Yin, 2014). Trying to explain why interorganizational big data technologies supported cooperative interaction dynamics in some cases and competitive interaction dynamics in others, my first analysis step was to operationalize this outcome variable through deductive coding from the literature (Gulati et al., 2012; Uzzi, 1997). In a second step, I identified two explanatory variables, that is, technology design and organizations’ motivation for technology adoption, through two iterative rounds of inductive coding (Eisenhardt and Graebner, 2007; Strauss and Corbin, 1990). In the third and final step, I related my outcome variable of cooperative or competitive interaction dynamics as operationalized in step 1 to the explanatory variables identified in step 2. The result is a model that explains how organizations’ motivations for technology adoption and specific technology designs conjoin to support either cooperative or competitive dynamics. I have summarized my analysis steps, their objective, main insights, and outcomes in Table II.

*Operationalizing outcomes: cooperative or competitive dynamics.* In seminal pieces on interorganizational collaboration, several characteristics have been associated with cooperative relationship dynamics. In relationally embedded ties, which typically show cooperative interaction dynamics, partnering organizations share high levels of trust, fine-grained information sharing, joint problem solving (Uzzi, 1997). I coded for these in my data. Yet, not all of these characteristics fit my empirical cases exactly. Thus, iterating between my data and prior theory of relational embeddedness (Granovetter, 1985; Uzzi, 1997) and interorganizational collaboration (Gulati et al., 2012), I identified two characteristics to mark cooperative interaction dynamics: high trust and the pursuit of common goals. I coded all case relationship on a four-point scale as high, rather high, rather low, or low trust and pursuit of common goals. These describe the relationship on a general level, independent of individual technology adoption.

Trust is the ‘belief that an exchange partner would not act in self-interest at another’s expense’, so that trusting partners ‘assume the best when interpreting another’s motives and actions’ (Mayer et al., 1995; Uzzi, 1997, p. 43). As such, trust responds to a deep belief in the integrity or benevolence of their partner (Mayer et al., 1995). I coded for trust by looking for three specific markers. First, interviewees often explicitly used the word ‘trust’ to describe a relationship (e.g., case relationship C) or similar words to indicate closeness between partners (e.g., case relationship E). Second, I was looking for markers that indicate integrity, for instance the ability to speak openly despite competitive concerns (e.g., case relationship B) or to manage relationships through informal agreements (e.g., case relationship A). For low trust, I looked for markers indicating a lack of integrity,
| Analytical step | Objective | Insights gained | Outcome |
|----------------|-----------|----------------|---------|
| 1. Theory-driven deductive coding for outcome variable | Operationalize outcome: collaborative dynamics as composed of trust and pursuit of common goals | For each case relationship, trust and the pursuit of common goals can be high, rather high, rather low, or low. | First-order codes as shown in step 1, Figure 2: continuum from high to low trust and high to low common goals |
| 2. Refine outcome variable | Bring trust and common goals of cases together to categorize cases as cooperative or competitive | Each case relationship shows multifaceted collaborative dynamics composed of high to low trust and high to low common goals | See Figure 1: 2 new concepts to describe collaborative dynamics; cooperative or competitive |
| 3. Data-driven inductive coding for explanatory variable 1 | Identify relevant technology design characteristics | Each case relationship demonstrates high, rather high, rather low, or low transparency symmetry and shared or unshared analytical processing capability | Theoretical categories as shown in step 2, Figure 2: transparency symmetry, transparency asymmetry, shared analytical processing capability, unshared analytical processing capability |
| 4. Refine outcome variable 1 | Bring technology design characteristics together to identify technology designs | Each big data technology has one design defined by either transparency symmetry or asymmetry and shared or unshared analytical processing capability | 4 possible technology designs; combining level of transparency symmetry and shared/unshared analytical processing capability |
| 5. Integration step 1: Match outcome with explanatory variable 1 | Establish whether technology designs can explain collaborative dynamics | Technology designs cannot on their own explain collaborative dynamics | 3 out of 4 technology designs show cases with both cooperative and competitive dynamics |
| 6. Data-driven inductive coding for explanatory variable 2 | Identify firms’ motivations for technology adoption | In each case relationship, firms can either share learning motivations or pursue complementary motivations | Theoretical categories as shown in step 2, Figure 2: shared learning motivations, complementary motivations |
| 7. Integration step 2: Match outcome with both, explanatory variable 1 and explanatory variable 2 | Establish whether firms’ motivation for technology adoption in conjunction with technology design can help explain collaborative dynamics | Technology design matters for collaborative dynamics where organizations share learning motivations / Where firms hold complementary motivations, collaborative dynamics are cooperative. | See Figure 3: Process model explaining how technology design and firms’ motivation for implementation jointly determine collaborative dynamics |
for instance the feeling that the partner will misrepresent themselves and their offering (e.g., case relationship J) or the need to specify and police concrete contractual terms in order to secure compliance (e.g., case relationship M). Third, I looked for markers that indicate benevolence, for instance the willingness to try new things despite not knowing exact performance outcomes (e.g., case relationship D) or the conviction that if an error occurs, the partner will do what is necessary to rectify it (e.g., case relationship I). For low trust, I looked for the absence of benevolence, for instance the belief that a partner would always primarily or exclusively seek self-interest (e.g., case relationship L) or purposefully seek to disadvantage the focal firm (e.g., case relationship K).

Similarly, collaborations marked by cooperative interactions tend to pursue primarily common goals. Following an earlier conceptualization, I define common goals as those that accrue collectively to all alliance participants, and private goals as those that accrue to subsets of the participants (Khanna, 1998). To some extent, such non-rivalrous pursuit of common goals requires fine-grained information exchange and joint problem-solving (Uzzi, 1997). Where organizations actively focused creating value for both partners (e.g., case relationship B) or furthering both organizations’ longer-term strategic goals (e.g., case relationship E), I coded this as common goals. Where organizations were largely concerned with achieving their own strategic goals, often by preventing their partners from achieving theirs (e.g., case relationship J), or where strategic goals were so distant that they were almost contradictory (e.g., case relationship I), I coded this as private goals.

From my reading of this literature, these two characteristics should be complementary so that a stronger orientation towards common goals can make up for a lack trust and vice versa. Collaborative dynamics are complex, and this division into an affective trust and a more cognitive joint interest dimension of cooperativeness should provide a balanced account of collaborative dynamics as being either cooperative or competitive (see Figure 1).

Inductive coding for explanatory variables. I then shifted to two rounds of inductive open coding across all case relationships in order to identify explanatory variables (see Figure 2).
coded inductively for constructs that appeared to be decisive in understanding the effects of technology adoption. Initially, multiple codes emerged from the data: for example, learning, control exertion, transparency, analytics capabilities, or power positions. In a systematic cross-case analysis of similarities and differences across cases (Eisenhardt, 1989; Eisenhardt and Graebner, 2007), I concentrated on the most insightful codes:
technology design characteristics transparency (a)symmetries and (non-)shared analytical processing capability, each coded on continuum from high to low. This way, I found that technology designs provided not always symmetric transparency and shared analytical processing capability, but often asymmetric transparency and unshared analytical processing capability.

My working hypothesis was that technology designs could explain collaborative dynamics, something that was disproven when I matched technology designs with collaborative dynamics: technology designs alone did not determine collaborative dynamics.

I, therefore, entered a second round of inductive open coding. In this instance, I noticed that organizations had distinct motivations for technology adoption and that these motivations could be identical for both partners, or complementary. I coded each organization in a given relationship as having a ‘learning motivation’ or an ‘efficiency motivation’, and then matched both partner firms’ motivations as theoretical category ‘shared learning motivations’ or ‘complementary motivations’. This became my second explanatory variable.

Jointly, the first and second explanatory variables allowed me to create a process model (Figure 3 in discussion) to answer my research question.

FINDINGS

My analysis reveals that each case relationship could be described by two explanatory variables and one outcome variable (see Table III). The firms’ motivation for technology adoption and technology design jointly explain when the introduction of interorganizational big data technologies support cooperative or competitive dynamics. In the following, I will first briefly introduce each explanatory variable. Then, I describe four paths in
Table III. Summary of case relationship categorization

| Company ID | 2 | 4 | 5 | 2 | 3 | 5 | 2 | 1 |
|------------|---|---|---|---|---|---|---|---|
| Relationship ID | A | B | C | D | E | F | G | H | I | J | K | L | M |
| **Collaborative dynamics** | | | | | | | | | | | | | |
| **Cooperative** |  + + + + + + + - - - - - - - | | | | | | | | | | | | |
| Trust |  + + + + + + + - - - - - - - | | | | | | | | | | | | |
| Common goals |  + + + + + + + + + + + + + - - - - - - - | | | | | | | | | | | | |
| **Competitive** |  | | | | | | | | | | | | |
| **Big data technology design** |  + + + + + + + - - - - - - - | | | | | | | | | | | | |
| Transparency symmetry |  + + + + + + + - - - - - - - | | | | | | | | | | | | |
| Shared analytical processing capability |  - - + + + - + - - - - - - - | | | | | | | | | | | | |
| **Motivation for technology adoption** |  | | | | | | | | | | | | |
| Compl. motiv. |  L | L | L | E | L | L | L | L | L | L | L | L | L |
| Shared learning motivations |  L | L | L | E | L | L | L | L | L | L | L | L | L |
| Complementary motivations |  L | L | L | E | L | L | L | L | L | L | L | L | L |
| Shared learning motivations |  L | L | L | E | L | L | L | L | L | L | L | L | L |

+ High; + Rather high; - Rather low; -- Low; L = Learning motivation; E = Efficiency motivation.
which the two explanatory variables come together to explain how interorganizational big data technologies foster cooperative or competitive dynamics.

**Big Data Technology Design and Technology Adoption Motivations**

As expected from my literature review, all big data technologies I studied have transparency and analytical processing capability at their core: sensors attached to heavy industrial equipment chronicle usage patterns and ambient conditions in order to represent and process data to learn from equipment operations for process optimization. However, I discovered significant differences in the extent to which technologies create symmetric or asymmetric transparency and shared or unshared analytical processing capabilities across partners. I provide illustrative vignettes of each explanatory variable in Table IV.

**(A)symmetric transparency.** All interorganizational big data technologies I studied create operational transparency: as the heavy piece of equipment is used in the production of industrial products or services it automatically generates digital traces that chronicle the production process. This creates transparency over equipment performance and usage, and then also over the production process itself. Yet, what differs across cases is who creates the representations and who can access source data and analytics processes. Where both partners have equal access to source data and analytics processes, the technology provides symmetric transparency. Where only one partner creates transparency and limits the other’s access to source data and analytics processes, the technology provides asymmetric transparency.

*Shared or unshared analytical processing capability.* The second technology design characteristic is the extent to which the interorganizational big data technologies create shared analytical processing capability for partners. Creating operational transparency over a product and service is only a preliminary step to allow learning – once organizations have created transparency, they need to analyse visualized processes separately or jointly. Where partners use the same interfaces, the technology provides shared analytical processing capability. Where one partner creates separate interfaces for themselves and their partner to interact, or each partner creates their own analytics interface, the technology provides unshared analytical processing capability.

My analysis further surfaced two alternative motivations for technology adoption, that is, learning and efficiency, and two distinct setups: one where organizations share learning motivations and one where organizations hold complementary motivations of learning and efficiency.

*Shared learning motivations.* In some relationships, both partner organizations adopt the interorganizational big data technology because they want to learn about a specific operational process or develop their proficiency in data analytics. Specific learning motivations may not be identical; one organization may want to learn about a specific operational process as its partner wants to learn about the data analytics that enables the learning about this process. Yet, both organizations consider the technology primarily as learning tool and evaluate it in terms of how much learning it provides.
Asymmetric transparency

In case relationship A the supplier of industrial data-based efficiency consulting services collects a limited amount of ambient data (e.g., location, three-dimensional equipment position). The customer complements these data by reading and entering additional pre-determined equipment data manually. All collected data are sent back to the supplier’s server site, where they are combined with external databases and curated to provide the supplier with a shared analytical processing capability. Every time the customer shares concrete operational data with the supplier, the supplier accesses this data and uses it to optimise their internal supply chain processes. The customer has no access to the supplier’s internal databases and is only able to observe their own simplified interface, which requires them to pass on the data in the same quality as received. The customer can observe their supplier’s operations and use these insights to make internal operational adjustments, but they do not systematically learn from this transparency. The customer can see how their supplier’s processes are adapted, but they do not have access to the supplier’s internal databases. The customer has greater and more systematic insights into their supplier’s processes. Analysing data across production sites, the customer learns continuously how to improve performance in a variety of ambient conditions. Both the customer and the supplier learn about operations, despite asymmetric transparency in the production process.

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Explanatory variable 2: Motivation for technology adoption

Shared learning motivations

In case relationship M the customer pays a contracted fee for the use of their supplier’s equipment and is contractually obliged to pay a share of operational costs. Yet, the supplier operates this equipment. Thus, the customer has an interest to reduce these operational costs. In rolling out their internal benchmarking system to their supplier, the customer intends to learn about specific operational processes in order to find optimization potentials. At the same time, the customer develops data analytics skills. The customer integrates recorded and transmitted data into their algorithmic learning program and comparing this supplier’s operations data to their aggregate data of all installations, pursues systematic learning. The supplier also wants to learn through the technology. They are interested in the insights and recommendations shared by their customer to learn about their concrete operational processes; for example, ways to reduce fuel consumption in operating equipment or to adjust specific equipment settings or cycle times to improve their input-yield ratio.

Complementary motivations

For the customer of the ‘efficiency consulting’ analytics service in case relationship D, the technology was the first step towards data-based learning. Making a small investment, the customer wanted to learn how minor adjustments to operations can affect operational cost savings. The technology collects a minimum of necessary data without complicated set-up and sends these raw data to their supplier to provide rudimentary insights into operations. Algorithmic analysis is limited to providing a limited overview of real-time equipment status: the technology captures and displays key operational metrics on a dashboard, which the customer uses in operational decision-making. Based on this insight, operational personnel at the customer site learn about their own operations. For the supplier, there is little opportunity to learn, but great potential to leverage existing resources and capabilities. The supplier maintains a range of highly sophisticated services across relationships and the technology in this relationship provides an opportunity to leverage existing infrastructure to provide an additional revenue stream for little investment on this slimmed down product. Data collected at the customer site is so rudimentary compared to their other services, that it provides little additional insights or potential for learning about data analytics.
Complementary motivations. Alternatively, partnering organizations can also pursue distinct but complementary technology adoption motivations. In this case, one partner organization pursues learning motivations about concrete operational processes or data analytics similar to the ones described above, while the other organization pursues pure efficiency motivations, aiming to reduce operational costs. Thus, the same technology is seen to provide two distinct, non-rival benefits to partnering organizations. In fact, the two complementary benefits are mutually reinforcing: for one organization to benefit from concrete recommendations or measures to improve their operational efficiency, their partner needs to have learned enough about data analytics and concrete operational processes to provide meaningful assistance.

My analysis suggests four paths that explain how firms’ technology adoption motivations and big data technology designs affect collaborative dynamics. When organizations pursue complementary motivations, collaborative dynamics tend to be cooperative (path 1). However, when organizations pursue shared learning motivations, technology design has a strong effect. The extent to which technologies provide symmetric or asymmetric transparency and shared or unshared analytical processing capabilities shapes collaborative dynamics (paths 2-4).

Path 1: Specialized Partnership

In specialized partnerships, one organization conceives technology adoption as a means for learning, while the other is interested in efficiency gains. On this path, collaborative dynamics do not depend on technology design, as both partners perceive technology mainly as a way to engage in mutually beneficial optimization. Case relationships A, D, E, F and G follow this path (see Table V).

This path is exemplified by case relationship E, where the supplier of industrial equipment uses the data to develop ‘predictive maintenance’ and ‘efficiency consulting’ services for their customer. The customer, in turn, adopts the technology for cost savings.

Case relationship E exemplifies how organizations hold complementary motivations for technology adoption. The supplier pursues learning objectives. Having previously sold their equipment to the customer, the supplier now offers added services to help their customer use the equipment more efficiently. In doing so, the supplier wants to learn how the customer uses the equipment and how well the equipment performs, ‘we can learn and understand how customers actually use the [equipment]. And learn about these incidents that typically cause a break down and what can be done to prevent those’ (TM, supplier). By learning about how equipment is used, under which conditions it is likely to breakdown, or how usage patterns relate to maintenance needs, the supplier can adjust their in-house research and development for their equipment and develop new data analytics services for customers. Furthermore, such detailed analysis helps the supplier develop their data analytics skills. Thus, the supplier understands the technology as means to learn about equipment use, equipment design, and data analytics.

For the customer, the key motivation is to increase production efficiency by reducing equipment downtime, operational, and maintenance costs, ‘the customer wants automated
Table V. Additional cases for path 1 ‘specialized partnership’

| Case relationship A | Case relationship D | Case relationship F | Case relationship G |
|---------------------|---------------------|---------------------|---------------------|
| **Efficiency consulting** | **Efficiency consulting** | **Predictive maintenance, efficiency consulting** | **Predictive maintenance, efficiency consulting** |
| The supplier of physical industrial services collects sensor data about their internal process and the customer’s status in this process. For this, the supplier receives detailed operations data from their customer. The supplier analyses data to optimize their internal operations. The customer has access to a wide subset of these data to plan their internal operations and monitor process progress at the supplier’s site. | The supplier provides a data-based analytics service to help customers optimize their physical operations. The supplier collects the customer’s operations data and curates them into real-time dashboards. The customer uses these data to make operational optimization decisions. | The customer buys equipment from the supplier and collects sensor data, analyses them for ongoing internal operations and optimization, and occasionally inspects data to re-evaluate supplier quality. | The supplier sells equipment and equipment related maintenance services. The supplier collects equipment operations data at the customer’s site via sensors, analyses them, and provides recommendations for optimized operations and maintenance to the customer. |

Collaborative dynamics

| Cooperative | Cooperative | Cooperative | Cooperative |
|-------------|-------------|-------------|-------------|
| Trust + + | + | - | - |

I just met a customer where we agreed that they pay their bills and in four weeks we sit together and I’ll help them. And that is enough, they don’t need a written agreement. In our industry that is still quite common [...] That is close and casual. And if I lied to them, I couldn’t do business anymore (TM, supplier)

They are willing to try it [the product], and of course our goal is to make this successful (OM, supplier)

We prefer partnering with nicer partners, but we negotiate and make decisions based on cost calculations (MM, customer)

I: How do you determine which kind of customer a customer is?
R: There is a certain logic, we look at certain parameters and that is with the growth potential, then we look at the revenues today. I mean growth and revenue from existing install base and future install base, so it’s really about future and today (OM, supplier)

(continues)
| Common goals | Case relationship A | Case relationship D | Case relationship F | Case relationship G |
|--------------|---------------------|---------------------|---------------------|---------------------|
| + +          | As long as the customer is here, they don't make any money and neither do we. We need to open up the slot for the next customer. Speed has a greater importance for customers than 10, 15 years ago (TM, supplier) | + | We need to keep in mind that even small things bring a lot of value to the customer […] This subscription-based model is so cheap (OM, supplier) | + + | Us showing them that we can offer a new service or better services and help you to become more efficient. Many times, in these contracts it is that, you have to help us and we promise you to, for instance lower your fuel consumption during a period of two years, with so many percent so they can be in the contract. Then we make it, but we also then make sure that they’re using our spare parts (TM, supplier) |

| Technology description | + | - | - | + |
| Transparency symmetry | + + | - | - | + |

| Technology description | + | - | - | + |
| Transparency symmetry | They want to know the exact status of their operations, whether the temperature is measured continuously, whether temperature is constantly in the optimal area, etc. (TM, supplier) | We don't give exact recommendations, we only give the transparency and they optimize by themselves (OM, supplier) | No, we are the only ones with access to these data. Sometimes our supplier asks to access them, but my bosses need to decide if we share the data (OM, customer) | Yes, in a way you’re getting, not too much the raw data but you’re getting outcomes, […] then if there’s getting the full transparency of what we’re doing and seeing in real time on a dashboard, then if we are messing up then they are seeing that we are messing up (OM, supplier) |
Case relationship A | Case relationship D | Case relationship F | Case relationship G
---|---|---|---
**Shared analytical processing capability** | | | |
- [paraphrased:] When our customer is late, they expect us to help them catch up this delay – to do our work faster. We receive detailed information about [our customer’s] goods electronically and [use these data when we process their goods]. The principles have been the same for the last 100 years, but new restrictions were added. And these details may change suddenly and we need to adapt – this [process] never stands still (TM, supplier)
- When I talk to this customer, I need to explain what is web application data, they are starting from the basics. They have used some excel, but that is it (OM, supplier)
- We have greater learning about equipment operations, we operate them in real-life conditions (OM, customer)
- On the general level, when you gather more information and you gather data, you get more experience on analysing it. So it’s wrong to say that it would have been stable for the past 15 years. Of course not. You develop the tools and you develop the insight and you develop the reports (…). It’s constantly changing the product (OM, supplier)

**Motivation for adoption**
**Focal organization**
**Complementary motivations**
**Learning**

[paraphrased:] We need to do our traditional activities at more exact data quality and speed. The IT-system needs to find a way to manage this with fewer personnel (TM, supplier)

**Efficiency**
And also in [the product line we sell to this customer], we reap the fruit of other cooperations [relationships]? (OM, supplier)

**Learning**
We wanted to know how our equipment works, so we developed a new performance measure (MM, customer)

**Learning**
This type of a new service has much shorter life span than (operational) equipment. If you bring our new service, it could be marketed and everybody wants to buy it, but then three years afterwards there are already competing products which are as good or even better, so you have to keep innovating, keep adding new features, keep making them better to fulfil the customer needs (OM, supplier)

(continues)
Table V.  Continued

| Partner organization | Case relationship A | Case relationship D | Case relationship F | Case relationship G |
|-----------------------|---------------------|---------------------|---------------------|---------------------|
| Efficiency            | For our customer it is extremely important to know about the process of service delivery because their customers want to know about this. They need to know what causes delays and what is the current status of the service process. Therefore, our customer wants transparency to see, can they do something? Who is responsible for delays? (TM, supplier) |
| Learning              | The starting level (of our customer’s knowledge base) is really low, and that is why we can bring value so easily (OM, supplier) |
| Efficiency            | When we meet, sure, we say ‘we want to purchase a new equipment type, which you also produce. You know you will be considered in the process, but you know, we are looking for a combination of quality (as measured by the indicator) and price. Make an effort’ (MM, customer) |
| Efficiency            | Also our customers were looking for our expertise on the installed equipment that how are they doing and are they optimally… is the configuration optimal for their environment and could they do something more or could they save fuel by doing something else. Based on this need, we started to develop, a condition-based monitoring project where we, understood that we need to have connectivity to on-site, because it’s… We can’t have a person on-site doing these things. The person needs to be a highly trained expert and needs to have a good understanding of the equipment, and all the sensors and all operations of that equipment. (OM, supplier) |
alerts from some critical things and they don’t want to follow the portal. They want to get information when to act and what to do’ (OM, supplier). The customer has no ambition to develop their own analytics solution, nor are they interested in learning what specifically caused inefficient equipment usage. They want concrete recommendations on how to modify equipment use in real-time to lower operational and maintenance costs in the long-term, as their supplier can independently modify maintenance intervals to a necessary minimum. The customer wants concrete measures for reducing costs, not learning. These distinct but complementary motivations for technology adoption void concerns over value learning asymmetries as long as both organizations’ objectives are met.

This path shows three different technology designs. Case relationship E deploys an asymmetric transparency/shared analytical processing capability design, case relationships D and F show an asymmetric transparency/unshared analytical processing capability design, and case relationships A and G adopt a symmetric transparency/unshared analytical processing capability design. Each design increases absolute transparency and/or analytical processing capability.

The five relationships on this path all show cooperative interaction dynamics. To illustrate, case relationship E demonstrates high trust, ‘the relationship is getting closer’ (OM, supplier), and the pursuit of common goals, ‘customers are more aware what has happened and they can find the root causes for the problems, and they can see remote services data (…) we can give recommendations earlier, improving this customer relationships’ (OM, supplier). Thus, I propose,

Proposition 1: Where organizations pursue complementary motivations for technology adoption, interaction dynamics will be cooperative irrespective of whether the big data technology provides symmetric or asymmetric transparency and shared or unshared analytical processing capability.

Path 2: Averted Learning Races

In averted learning races, both organizations implement the technology with an intent to learn through it. Big data technologies provide symmetric transparency and shared analytical processing capability. Having access to the same data and shared analytical processing capability, organizations feel they have equal opportunities to learn and gain from technology adoption. In this study, case relationships B and C followed this path.

Case relationship B (for additional case relationship C see Table VI) implement the technology for ‘efficiency consulting’. The supplier provides a sophisticated data-based analytics service that helps their customers optimize their physical industrial services operations through optimized equipment operations.

Organizations pursue shared learning motivations for technology adoption. The supplier sees the technology as tool to develop their core capability of data analytics as well as their understanding about the customer’s concrete operational processes. Understanding both data analytics and the customer’s operations are prerequisites for continued relevance and accuracy improvements of their service offering, ‘we have learned so much from [this] customer (OM, supplier)’.
The customer equally pursues learning motivations. First, learning directly from the dashboard and recommendations shared by their supplier, the customer learns about concrete operational processes and ways to improve operational efficiency. Second, the
customer has their own internal data analytics unit and works together with the supplier to further develop the service. The customer engaged actively with their supplier, ‘they have smart people, they can challenge us’ (OM, supplier), with the concrete motivation to develop their data analytics skills, ‘that is pretty much our [my team’s] basic task to make our fleet the most energy-efficient within the industry and to look for more technologically disrupting technologies, keep further enhancing the efficiency of our operations’ (OM, customer).

The technology provides symmetric transparency into digitally enhanced operational processes; both the supplier and the customer have access to and analyse the same data, ‘they [the customer] are more technology… not savvy, but open to using it and also then analysing the data, and I know that they are analysing a lot of [operations-related] data, doing their complicated algorithms, and so on’ (MM, supplier). The organizations both observe the same data for their own internal analysis as well as for occasional joint analysis.

The technology further provides shared analytical processing capability, even to the extent that the customer actively participates in shaping the shared interface. Customers help their supplier decide how data may best be analysed and which data to curate in dashboards. The supplier-provided dashboards also automatically indicate how the implementation of recommendations affect performance, providing the customer an easy monitoring tool of supplier performance. This constitutes a high degree of shared analytical processing capability: As a result, both organizations learn independently and jointly from using and interacting through the technology, ‘they [the customer] are product development partners. We have been growing together for many, many years’ (OM, supplier). The technology facilitates specific agreed-on interactions and knowledge exchange to jointly optimize a particular, well-defined process with the clear aim of giving recommendations. This allows the exchange of knowledge for joint optimization and learning.

Case relationship B exemplifies cooperative interaction dynamics marked by trust as evidenced in this quote, ‘it has been an open communication and partnership. Of course, we need to be careful, but we can speak quite openly’ (OM, supplier), and the pursuit of common goals, ‘we took the step of being a first mover, we shared all our data, to help [our supplier] to improve, to polish some of the tools developed for us. Our first mover approach means that we get the new product much in advance compared to our competitors’ (OM, customer). Thus, I propose:

**Proposition 2:** Where organizations pursue shared learning motivations for technology adoption, interaction dynamics will be cooperative if big data technologies provide shared analytical processing capability and symmetric transparency.

**Path 3: Suspicious Learning Races**

In suspicious learning races, both organizations implement the technology with an intent to learn through it. Big data technologies create asymmetric transparency but shared analytical processing capability. While shared analytical processing capability provides equal learning opportunities, asymmetric transparency creates distrust between partners over equitable value capture. This creates competitive dynamics. Case relationships L and M follow this path.
In case relationship L (for additional case relationship M see Table VII), the customer purchases industrial equipment with lifecycles of several decades at irregular intervals. The customer’s ‘predictive maintenance’ technology collects sensor data to visualize and optimize equipment use and related operational processes.

Both organizations pursue shared learning motivations with technology adoption. The customer uses the technology for equipment purchased from this supplier and other suppliers at their production site. Aiming to create a company-wide information system that visualizes, analyses, and helps optimize equipment operations at all internal production sites, the customer wants to learn about concrete operational processes and how to run them more effectively. Furthermore, the customer wants to develop their data analytics skills to develop and manage a company-wide optimization information system. Given their vast number of industrial equipment suppliers, the customer sees these two learning points as critical for long-term company success, ‘we have about ten to fifteen suppliers of equipment [on-site], so we really cannot afford to have ten or fifteen standalone solutions’ (OM, customer). They choose to develop a proprietary platform for managing learning and collaboration centrally in-house. Recognizing the need to draw on their supplier’s equipment-specific expertise for predictive maintenance solutions, the customer includes their supplier in the development of one such analytics solution.

The supplier agrees to implement this technology because they are equally interested in learning about data analytics in order to expand their ‘predictive maintenance’ digital service offering, ‘suppliers are looking to sell us the solutions, condition monitoring, and looking to develop their own predictive analytics’ (OM, customer). Thus, the supplier sees collaboration on this technology as a means to learn about data analytics in a necessary step towards expanding their digital service range.

The big data technology provides asymmetric transparency. The customer had bought the physical equipment from their supplier, uses it within their firewalled internal production sites, and has therefore exclusive access to the data generated by the equipment. Data are generated, stored, and analysed internally on servers at the customer’s production site. To get access to their supplier’s capabilities, they share those operations data necessary for the joint development of predictive maintenance solutions. In doing so, each company visualizes the data in their own systems, displaying to the other only what is necessary. Yet, the customer has more extensive data access. During negotiations and other meetings, they can regularly draw on additional sensor data not previously shared with their supplier. The customer also often compares sensor data from this supplier’s equipment to data of their competitors’ equipment, ‘now that data we then take and turn around towards the suppliers because we can sit and benchmark the different suppliers across our businesses’ (OM, customer). This shows that the customer has a much better insight into operations and the broader environment than they share regularly with their supplier. Thus, both organizations do their analytics on somewhat different datasets. The customer has continuous access to a broader dataset and only occasionally shares additional data with their supplier, often during negotiations to leverage their bargaining power.

The relationship further involves shared analytical processing capability. The partners perceive a need to work together and to create a shared interface to combine their separate analyses. This affords new learning opportunities for both sides, ‘without us, the supplier could not have a comfortable ground to develop their solutions, to test it in real life. They
Table VII. Additional case for path 3 ‘suspicious learning race’

| Case relationship M |
|---------------------|
| **Efficiency consulting** |
| The supplier provides physical industrial services. The customer collects sensor data on their suppliers’ physical operations, analyses these data, and provides operations recommendations to their supplier. The contract is a fixed fee, but the customer shares some of their supplier’s operational costs. Operations recommendations aim to reduce these operational costs. |

| Collaborative dynamics | Cooperative |
|------------------------|-------------|
| Trust                  | − −         |
| You needed to force the technical management to pay attention to this. Otherwise they simply wouldn’t do it because it was just extra work in a hectic day, and I fully understand. They needed to understand that their management would look to them for results. (MM, customer) |

| Common goals | − −         |
|--------------|-------------|
| And if [our digital service people] have issues [getting the supplier to follow recommendations], they can always, you could say, ask for leverage with our [commercial] department because, of course, they have the commercial angle, and they can push a little bit if they need some incentive…’. (OM, customer) |

| Technology description | Transparency symmetry | + + |
|------------------------|-----------------------|
| I think if it comes to operational data, we know much more, and we analyse much more, and we see much more. (MM customer) |

| Shared analytical processing capability |
|----------------------------------------|
| On top of that, when we see that, if some [key personnel] need some special care or guidance, then we go [on site] to assist them. They let us, let the performance manager come [on site] and look at the (pings) themselves and talk to them, you know, and guide them what to do, how to do. And finally, in some cases, we have to call the [manager in charge] to the office as well for, for, for you know, for, for a session on performance. (OM, customer) |

| Motivation for adoption | Complementary motivations |
|-------------------------|----------------------------|
| Focal organization | Learning |
| You can say from our perspective, from the performance optimization perspective, we just looked at the [equipment] groups. So we would basically just produce a score card, and we would go internally and say, you know, well, this group is not doing very well. They have this potential for optimization, and they would be measured on it. (OM, customer) |

| Partner organization | Learning |
|----------------------|----------|
| ‘[After sending scorecards to all the suppliers…] There was a lot of positive reception. Of course, the one who were called bad, they were not that positive, but we had a dialog. And we could say what are the pain points. What can we do to mitigate pain points?’ |
only do it in the labs. And without the suppliers’ active innovation and initial investment, we will not able to, be able to benefit from this technology as well’ (OM, customer). Thus, despite asymmetric transparency, the sharing of analyses provides both companies with significant learning.

Organizations learn to a similar, if not equal, extent. Nevertheless, they demonstrate competitive interaction dynamics. The level of trust between managers is low as interactions are often reduced to contractual negotiations, ‘we are currently in the process of changing our contractual [terms] to make sure that we own the data and can access it’ (OM, customer), and organizations seem more interested in their own goals rather than shared ones or those of their partner, ‘so when it comes to negotiating equipment prices, we can basically then leverage our power and say, we have the information available’ (OM, customer).

Jointly the two organizations analyse digital data to optimize equipment operations. In this effort, both organizations learn and benefit: the customer saves operations costs and the supplier learns more about how to design, operate, and maintain their equipment. Yet, the organizations are suspicious whether benefits from this symmetric learning are allocated and divided ‘fairly’ across partners. A manager from the customer company expresses it this way: ‘we can supply [sensor data] for continuous improvements. But then that tells me that we do need certain benefits’. I’d say that’s the one area, and that’s why we do have this contractually included’ (OM, customer). Where organizations share a learning motivation, shared analytical processing capability that builds on asymmetric transparency may cause suspicion between partners, triggering competitive dynamics. Thus, I propose,

*Proposition 3:* Where organizations pursue shared learning motivations for technology adoption, interaction dynamics will be competitive if big data technologies provide shared analytical processing capability but asymmetric transparency.

### Path 4: Realized Learning Races

In realized learning races, both organizations implement the technology with an intent to learn through it. Big data technologies create unshared analytical processing capability, which renders collaborative dynamics competitive: as both organizations measure the success of the relationship at least partly in learning, the lack of shared analytical processing capability prevents equal or even similar learning between partners. Even in cases where neither organization explicitly attempts to outlearn the other, unshared analytical processing capability means developing competitive interaction dynamics. In this study, case relationships H, I, J and K follow this path.

To illustrate, in case relationship J (for additional case relationships H, I, K see Table VIII), the customer purchases ‘predictive maintenance’ data analytics services for equipment operation recommendations from their supplier. Traditionally, the customer had purchased industrial equipment from the supplier. The new technology allows optimized maintenance of these purchased equipment and those purchased from other suppliers.

Both organizations hold shared learning motivations for technology adoption. The customer initially hired their supplier to build the data analytics solution on a third-party information technology infrastructure in order to assure migrating the learning
Table VIII. Additional cases for Path 4 ‘realized learning race’

| Collaborative dynamics | Case relationship H | Case relationship I | Case relationship K |
|------------------------|---------------------|---------------------|---------------------|
| **Predictive maintenance, efficiency consulting** | The supplier sells equipment and then collects data from their customers’ operations, analyses them and provides recommendations for optimized operations and maintenance remotely as service | The supplier sells equipment. The customer then collects equipment operation data, analyses the data, and uses insights to optimize equipment operations and maintenance. Occasionally these data are used for relationship management (e.g., future contracting, negotiations). | The customer buys a physical industrial service and collects digital data on this process to constantly monitor and analyze their supplier’s performance. The supplier collects and analyses the same operations data, but they do so on different systems and do not share the data, nor their analyses. |
| **Competitive** | Occasionally we have difficulties. For instance, in the construction phase, we might have given wrong or bad specifications – just because we didn’t know any better. That can happen. And the supplier [shows flexibility because they] have an interest to look good and to be chosen also next time. (MM, customer) | Some new features or functionalities are developed in these delivery projects as well. So, in that kind of projects there are typically some new functionalities, every now and then that are implemented. And, of course, those machines are, somewhat tailored anyway, always, to match customer needs. So, there’s always some kind of development. (OM, supplier) | They [the customer] would use all of this data to play out the [competitors]. (OM, supplier) |
| **Trust** | The IT guy could ask the question (…) if we tweak a little bit what you are asking, but again these discussions are not happening that much because it is a dilemma that customers who are asking this have also this thing about data sensitivity, they are not willing to give their data (because of the business risk). (MM, supplier) | This constant development… and measurement of how the equipment develops over its lifetime, is not of interest to us. They of course are very interested. (MM, customer) | Just the fact that we showed that we are interested in this performance has a tremendous value for them. Even if we haven’t actually documented a lot of improvements now, it demonstrates a mindset. (OM, supplier) |
| **Common goals** | | | |

(continues)
### Table VIII. Continued

| Case relationship H | Case relationship I | Case relationship K |
|---------------------|---------------------|---------------------|
| **Technology description** | + | − | − |
| Transparency symmetry | [The customer] are strongly requesting that we just feed our data to their system [...] But they are also very sensitive about their very critical data. (MM, supplier) | We like to keep our decks closed. Of course, we collect these data [on a centralized level]. When we talk to the manufacturers, we also discuss these data. But generally, we don’t provide them [...]. (MM, customer) | We are constantly met by this client, who said ‘how come your [operational performance indicator] last Tuesday were off the chart?’ (OM, supplier) |
| Shared analytical processing capability | − | − | − |
| Motivation for adoption | Shared learning motivations | Shared learning motivations | Shared learning motivations |
| Focal organization | Learning | Learning | Learning |
| We are a long-time player in this industry. We have very good knowledge about the things. We have been a world-leading company in some areas. Now we need to implement some portion of this digitalisation, it touches almost every field of engineering. (MM, supplier) | We measure how often a [piece of equipment] performs sub-optimally [as measured by indicator A]. Maybe we find a way to improve on this? (MM, customer) | We wanted to know the most about the processes that we were supposed to be good at, that we’re responsible for. (OM, supplier) |
| Partner organization | Learning | Learning | Learning |
| This customer has an organization to crunch this data. (MM, supplier) | [Paraphrased:] We need to analyse the data and base intelligent decisions on this [...]. The equipment needs to be intelligent enough to tell me why the red alarm goes off. (TM, customer) | [Our customers say:] we can see from our performance statistics that it’s actually a little bit slower than your competitor, so why… (OM, supplier) |
into the customer organization as the technology matures. They wanted to buy the base functionality from the supplier in order to learn about concrete operational processes, but to extend this in the long-term with an in-house developed extension of additional analytics functions. Thus, in the short-run, the customer’s intention was to learn about specific operational processes and in the long-run to learn about data analytics, ‘the reason why we chose to work with [this supplier], is that it also comes with a platform where we can then extend that product’ (MM, customer). However, this migration of learning has not occurred yet.

The supplier is interested in building this new ‘predictive maintenance’ and related ‘efficiency consulting’ data analytics service, which requires extensive learning across customers, production sites, and industries, in order to provide a high-quality service in the future, ‘our supplier, they have twenty thousand software developers… the real predictive maintenance looks at and analyses all of these parameters in real time’ (MM, customer). Thus, for the supplier, each technology deployment in each customer organization is an instantiation of learning about data analytics and different operations-specific environments.

The big data technology in case J provides symmetric transparency. The customer collects digital traces on their production sites, transfers the data to a cloud storage, where the supplier analyses it in order to provide recommendations back to the customer. Both, the customer and the supplier have full access to the digital data, ‘Interviewer: when [your partner] is analysing the data, you have agreed with the equipment providers to give you the data, and then you give the data to [your partner], and then they analyse it? Interviewee: Yeah […] So the data sits within IT. That’s looked on as an IT infrastructure component’ (OM, customer). The supplier in charge of designing the technology has built it to facilitate few points to interact with their customer, keeping the actual analytics largely contained within their own organization. The supplier only displays operational recommendations to their customer, which allows the customer to learn about their operations.

The case example represents an unshared analytical processing capability. The supplier gives recommendations via a dashboard, providing concrete insights into how to adjust equipment operations to increase performance, ‘they have an alert system saying if I’m driving the equipment too fast or too hard the system generates advice: “if you continue to drive the equipment the way you drive it, then we’ll have to stop the operation to do some maintenance within the next ten hours or two days or week when normal maintenance is not planned before next month”’ (MM, customer). However, the supplier’s analysis methods remain opaque to the customer. While the customer has full access to the digital data, they do not do the same kind of analytics. The customer’s ability to analyse these data is limited by their in-house expertise and the technology design that locates analytics practices solidly within the supplier organization. Furthermore, while the supplier provides dashboards to their customer, these are used only within the customer organization, the supplier uses their own separate technology interface. In consequence, the supplier learns about data analytics and process efficiency with every recommendation they give, while the customer’s learning is limited, ‘the black box [of data analytics] is moving to [our supplier]’ (MM, customer). This creates unequal learning opportunities across partners, which causes frictions.

Case relationship J shows competitive interaction dynamics, marked by low trust, ‘working with these mega vendors, it’s not always that you then get what you actually envisage’ (OM, customer), and the pursuit of primarily individual goals, ‘we are forced to take a route
where we go with different partners with the challenges, and sharing our value, and all these discussions that come along with that’ (MM, customer).

In this path, the defining variables are a shared learning motivation paired with unshared analytical processing capability, regardless of transparency (a)symmetry: my data show cases where the technology provides symmetric transparency (cases H and J), as well cases where the technology creates asymmetric transparency (cases I and K). All four cases H, I, J, and K demonstrate competitive interaction dynamics. Thus, I propose,

**Proposition 4:** Where organizations pursue shared learning motivations for technology adoption, interaction dynamics will be competitive if big data technologies provide unshared analytical processing capability.

**DISCUSSION**

These findings contribute to strategic management theory in two ways. First, I theorize a process model to understand how technology adoption motivations and big data technology designs affect collaborative dynamics (see Figure 3). Comparing path 1 with paths 2 to 4 shows that technology adoption motivations shape the way technology characteristics influence collaborative dynamics. Second, comparing paths 2 to 4 draws attention to the data sharing and processing capabilities in big data technologies as important influences on the emergence of learning races in digital environments. These observations apply and extend the established strategic management theories to the digitalizing world (Lanzolla et al., 2020).

**Interorganizational Big Data Technologies Shape Learning and Collaborative Dynamics**

The above findings suggest a process model for understanding how the introduction of interorganizational big data technologies affects collaborative dynamics. When organizations have complementary motivations of learning and efficiency, any big data technology design generates collaborative dynamics. In path 1, the technologies formalize concrete information sharing, decision-making and operational processes to solve a predetermined, well-defined operational problem. This helps solving a coordination problem of deliberately aligning partners’ actions to achieve jointly determined goals (Gulati et al., 2012, p. 537). Organizations focus on the benefits of absolute increases of transparency and analytical processing capability, which renders asymmetric learning unproblematic. Digital transparency mainly fulfils an input function to learning (Larsson et al., 1998), so that greater digital transparency (Lee, 2017; Lycett, 2013; Mayer-Schönberger and Cukier, 2014) and analytical processing capability (van Rijmenam et al., forthcoming; Zeng and Glaister, 2018) allow greater and faster learning (Schildt, 2017). In consequence, technology use is non-rivalrous and creates virtuous cycles of learning and efficiency: one organization’s learning helps their partner achieve desired increases in efficiency.
Extant literature on learning in alliances often assumes that partnering organizations may contribute different resources and capabilities (Dussauge et al., 2000; Hennart, 1988), while still pursuing the same learning motivations (Anand and Khanna, 2000; Gulati et al., 2009; Kale et al., 2000). However, interorganizational relationships can be asymmetric (Lumineau and Oliveira, 2018) not only in their resources and capabilities, but also in their objectives. Organizations might pursue distinct, complementary motivations when adopting big data technologies and this can be beneficial for bringing about cooperative dynamics.

When both organizations share a motivation to learn through technology adoption, technology design has a stronger effect on collaborative dynamics. Paths 2 to 4 show learning race dynamics where big data technologies pose a cooperation problem of jointly pursuing (learning) goals and distributing related contributions and payoffs (Gulati et al., 2012, pp. 533–34). This shifts the focus onto the perceived fairness of value capture from learning through technology adoption. Here, big data technologies’ greater transparency and analytical processing capability also lead to greater and faster learning, but both organizations measure technology success by the same outcome – learning. This focus on shared goals for the technology shifts organizations’ attention on the relative increases in transparency and analytical processing capability. Consequently, any asymmetries in learning outcomes are likely to trigger competitive interaction dynamics and a learning race (Hamel, 1991; Khanna et al., 1998).

In such contexts, the ex-ante technology design matters: big data technologies’ ability to collect and share data either symmetrically or asymmetrically affects collaborative dynamics differently than their ability to provide shared or unshared analytical processing of these data. While analytical processing capability situates learning either between or within organizations, (a)symmetric transparency represents an input to learning and a potential concern over equitable value capture from learning.

**Transparency as Extension to Learning Race Theory in Digital Environments**

A closer reading of paths 2 to 4 shows that existing learning race theory can only explain paths 2 and 4, but not path 3. The reasons for this lie in the previously understudied nature of interorganizational big data technologies. In line with prior theory (Lycett, 2013; Schildt, 2017), my analysis shows that big data technologies’ increased transparency and analytical processing capability foster faster and greater interorganizational learning. Yet, this work has to date overlooked the different effects of (a)symmetric transparency and (un)shared analytical processing capability for collaborative dynamics.

Paths 2 and 4 comply with extant theory’s account of learning races. Path 2 shows what I term ‘averted learning races’. Where big data technologies provide shared analytical processing capability, they situate learning between organizations and, therefore, provide equal opportunities to learn to both organizations. Organizations engage around the same visualizations, so that learning occurs primarily through joint analyses between organizations. When this big data technology further provides symmetric transparency, both organizations have equal access to underlying data and analytics. Thus, throughout the analysis process, both partners can refer to the source data for additional insights or
evaluation of the broader situation. This equal opportunity for partners to engage with the underlying data, creates a climate of openness among partners. While the shared analytical processing capability creates equal learning opportunities for partners by situating learning between organizations so that no partner systematically outlearns the other, symmetric transparency makes partners feel the created value from learning is captured fairly across partners. The technology thus formalizes a matching of two highly collaborative learning strategies between the partners (Larsson et al., 1998), which renders collaborative dynamics cooperative (Hamel, 1991).

Path 4 shows what I term ‘realized learning races’. Big data technologies provide different visualizations to both partners, either because both partners use different source data in the cases of technologies providing asymmetric transparency or because both organizations use the same source data but process these differently in cases of technologies providing symmetric transparency. In any case, unshared analytical processing capability situates learning within each organization individually so that organizations lack the space for joint analysis. This lack of shared analytical processing capability reflects less collaborative learning strategies of partners (Larsson et al., 1998), affording unequal learning opportunities. As organizations learn asymmetrically, learning races occur, rendering collaborative dynamics competitive (Hamel, 1991; Khanna et al., 1998; Larsson et al., 1998).

Path 3 provides an extension to learning race theory in digital environments. Prior treatment of learning races has seen transparency primarily as input to analytical processing and as endogenous managerial choice (Larsson et al., 1998). While this made sense in a pre-digital context, it does not hold in digital environments. Path 3 challenges both these assumptions. First, transparency is not only an input to analytical processing capability, but its symmetry is also an important determinant for collaborative dynamics. Where big data technologies provide shared analytical processing capability that situate learning between organization to afford equal learning opportunities, asymmetric access to underlying source data and analytics fosters suspicion among partners. I theorize that this is because partnering organizations cannot easily evaluate whether benefits from symmetric learning are divided fairly or whether partners potentially limit each other’s learning by sharing only a subset of relevant data. Such suspicion over equal value capture or partner’s integrity and honesty sows seeds of doubt and reduces trust between partners (Mayer et al., 1995). Collaborative dynamics are then competitive.

Second, as a central input to interorganizational learning, transparency has been seen as a managerial choice endogenous to collaborative dynamics (Hamel, 1991; Larsson, 1998). In the digital era, however, transparency can depend on a relatively fixed design of technologies. This makes symmetric transparency in technology design an important determinant for cooperative dynamics in learning races in digital environments. With this insight I advance knowledge in the alliance learning literature by refining it for digital environments (Baum and Haveman, 2020; Lanzolla et al., 2020; Schildt, 2017).

Limitations and Future Research

My qualitative research design has surfaced several insights, while also showing some limitations. Jointly, these limitations and contributions sketch three areas for future research:
big data technologies and changing work practices, human-machine learning processes within and across organizations, and a greater understanding of how big data technologies unfold across different contexts.

First, this is a qualitative study that showed how big data technologies shape work practices. I carefully selected a range of companies from the industrial services and equipment sector to make my findings analytically translatable to similar settings, but they are by no means generalizable. However, this qualitative design has allowed me to identify relevant variables of interorganizational big data technologies that affect strategy practice. Big data technologies are often considered as monolith with grand effects on overall theories. However, my findings show that we need to unpack big data technologies in an effort to understand its different components, and the ways in which they affect or adjust received theory. Thus, big data technologies do not change entire theories, but add to or adapt extant theories in digital environments (Lanzolla et al., 2020). Future research should assess how different elements and functionalities of big data technologies affect work practices. Furthermore, while my study has theorized the effects of one type of interorganizational big data technologies on collaborative dynamics, it does not address how the different paths affect firm performance. Future research needs to analyse performance outcomes of the different paths. Yang et al. (2015) have shown positive short-term effects for learning race winners despite competitive dynamics. However, long-term effects on focal firm profitability or the innovative capacity of the dyad are unknown. Collaborations are often seen to drive innovation, likely requiring cooperative dynamics (Doz, 1996; Uzzi, 1997).

Second, while my data were collected largely from only one side of the relationship dyad, this study points to interesting insights about human-machine learning in digital environments. Single-sided data are a common shortcoming of studies on interorganizational relationships (Lumineau and Oliveira, 2018) and while it would have been valuable to collect more extensive data from both sides of the dyads, it was not possible due to the high strategic importance and secrecy organizations place on this topic. I tried to mitigate this by selecting an equal number of customer and supplier focal firms and collecting partner interviews where possible. As these technologies become more widespread, future research might be able to collect dyadic data to validate and expand the insights in this study. Yet, my contribution to learning race theory in digital environments invites more research on the topic. Future research could refine dyadic insights by zooming into big data technology use within a dyad.

Such closer analysis might lend itself to a stronger process perspective (Langley, 1999) to unpack the learning process and uncover the concrete interactions and practices involved. A stronger processual view is of even greater interest considering that partner motivations and goals evolve over time. Furthermore, it would be interesting to explore whether and how organizations adapt governance mechanisms or technology designs in response to more cooperative or competitive dynamics.

Future research may also explore intra-organizational human-machine learning processes. For instance, it would be of great interest to theorize the concrete practices in which managers engage with big data technologies to bring about human-machine learning (Baum and Haveman, 2020). Another interesting avenue would be to consider how such augmentation affects interpersonal and group learning processes. Furthermore, a
comparative analysis of inter- and intra-organizational human-machine learning processes could uncover the ways in which big data technologies act as boundary objects to bridge different epistemic communities (Carlile, 2004).

Third, my empirical context is limited to Northern Europe. The findings are analytically translatable to other economies marked by high connectivity and availability of computing power and analytics skills, such as the broader European context or North America, but their applicability to emerging economies is limited. Related issues to address pertain to how national, sector and organizational culture affect managers’ understanding and implementation of these technologies, or how the institutional and cultural embeddedness of big data technologies affects their development and adoption.

Finally, future research could analyse interorganizational big data technologies within their information infrastructures (Constantinides et al., 2018; Henfridsson and Bygstad, 2013; Tilson et al., 2010). Given big data technologies’ modular nature and global reach, they are deeply entwined with broader socio-technical systems that condition their implementation and effects. One issue to explore is the extent to which the presence or absence of legacy infrastructures hinders, drives, and affects the introduction of big data technologies. Another avenue might be to investigate to what extent my findings translate from the dyadic to triadic, networks, or ecosystem-level. Balancing complementary technology adoption motivations and value capture from learning may become increasingly complex with an increasing number of partnering organizations, and their different governance modes. In addition to in-depth case studies to uncover the specific mechanisms of novel phenomena (Eisenhardt and Graebner, 2007), we also need larger quantitative studies on industrial interorganizational big data technologies across different contexts.

Implications for Managers

This study illuminates the importance of conscious technology design choices for collaborative dynamics. While it may be common to delegate technology design to engineering, managers should treat data transparency and shared analytics capability as strategic choices, in particular when their partners are motivated to engage in interorganizational learning. Developing greater transparency among the partners can facilitate collaborative dynamics, while partnerships involving technologies with asymmetric transparency can benefit from a clear agreement that one partner is pursuing optimization rather than learning to facilitate cooperative interaction dynamics. Thus, managers should be clear about their own and their partner’s technology adoption motivations and agree with their partner on goals and the division of created value. While big data technologies themselves are only one factor among many in determining whether partnerships become cooperative or competitive, they represent an important factor managers ought to be aware of.

CONCLUSION

This study explored how the introduction of interorganizational big data technologies allowing varying extents of transparency and shared analytical processing capability affects collaborative dynamics. Regardless of technology design, when one of the collaborating
organizations had a learning motivation but the other one didn’t, technology increased the efficiency of the relationship and facilitated cooperative dynamics. In relationships where both organizations had a learning motivation, technology focused attention to the relative benefits gained by each organization and fostered learning races. In fact, learning races were only avoided when organizations had symmetric transparency combined with shared analytical processing capability. Such technology facilitated joint learning and fostered a collaborative dynamic. These findings contribute to our understanding of big data technology use in alliances and introduce transparency as extension to learning race theory in digital environments.

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