Master Thesis in Business & Management

Nudging and Governing Big Data Solutions:
An explorative multiple-case study on how big data solution suppliers and buyers manage efficient relationships

Authors:
Caroline Sandblom (24210)
Keyang Tang (42074)

Supervisor:
Sven-Anders Stegare

Stockholm School of Economics
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Abstract

This qualitative study aims to explore how buyers and suppliers of big data solutions manage efficient relationships using governance mechanisms and nudging. A multiple case study was conducted through interviewing 12 organizations (buyers and suppliers) within the scope of big data solutions. First, the findings show that suppliers use governance as substitutes to manage data capability uncertainty through contracts that are within a narrow predetermined scope to restrain the effort required while still creating business value. They also start with easy and mature solutions as a way to extend the relationship where the buyer can purchase more advanced solutions later on. Second, buyers use contractual and relational governance as complements to manage data capability uncertainty by emphasizing both splitting payments into smaller parts and seeing the relationship as a mutual learning process. Last, the findings imply that suppliers use nudging to manage high expectations resulting in buyers purchasing less complex solutions. This study highlights the importance of buyer-supplier interaction to ensure efficient procurement of big data solutions. The results of this study may be adapted to other data management contexts and used as a reference point in terms of the improvement of data management and digital transformation.

Keywords: Big data; nudging; contractual governance; relational governance; private-private relationships

Authors:
Caroline Sandblom (24210)
Keyang Tang (42074)

Supervisor:
Sven-Anders Stegare, *PhD Student*, Department of Marketing and Strategy

Examiner:
Grading Committee, Department of Marketing and Strategy

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Sincerely,
Caroline and Keyang.

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1. Introduction

With the growing data power and digitization rate, the potential value creation of big data applications is boosted by reinforced data competence, including evolutionary technological progress, fulfilled data foundation and big data mindsets (Brunetti et al., 2020). Today, more and more companies see procurement of big data solutions either as the right answer to solve a business problem that a company has or as a competitive tool to stand out in their markets and industries. More specifically, among these demands, some companies intend to improve internal efficiency with the use of automation, while some companies pursue an advanced business model empowered by big data management. Compared to traditional services, big data solution procurement offers the digital value add-ins and smart control management, while more efficient data management enables organizations to gain insights that are valuable for their operations (Ziora, 2015). Accordingly, as a crucial component of digital transformation, an efficient big data application puts pressure on internal data efficiency in the buying organization, as it requires a higher level of integration and cooperation with regards to company data. Moreover, another trend is that more buyers are looking into boosting a specific data capability and search for niche digital solution suppliers to settle specific business problems or reinforce a specific dimension of data capabilities. Such demands intensify the market heterogeneity for big data solutions with the growth of customized data solutions and big data applications. This lowers the market entry levels, but on the other hand, raises higher requirements and more motivations for existing big data incumbents to improve service quality and outcomes of the big data solution application.

Why is it important to study the application of digitalization in private companies? Because there is a high failure rate in the process of applying big data solutions as well as in the whole process of the digital transformation (Brunetti et al., 2020; Westenberger et al., 2022). Corresponding with the big data demand hype, we see an increase in data service providers as there is a big data solution offering hype and a continuous increasing trend in the amount of big data solution consultancy companies. Despite promising market growth, there is a high risk of failure observed to proceed with big data solutions. Moving on, why put focus on the relationship between buyers of big data solutions and their suppliers? This study highlights how high-quality buyer-supplier relationships manage obstacles in automation processes and data-oriented value creation. In this study, a motivation bias and two uncertainties were identified: a motivation bias, a data capability uncertainty, and a digital ecosystem uncertainty.

This thesis aims to explore how buyers and suppliers of big data solutions mitigate biases and uncertainty using governance mechanisms and nudging to lower the risk of failure. The research question is as follows:

How do big data solution suppliers and buyers manage efficient relationships using governance mechanisms and nudging?

To answer this question, this thesis focuses on how big data solutions providers within the Swedish private sector deal with their relationships with potential buyers and current customers. In this regard, this explorative study incorporates buyer and supplier perspectives into one model and contributes to governance literature by exploring a fairly unresearched area: data acquisition and data transformation in private-private relationships. Also, this study contributes to nudging literature by exploring cognitive biases in a new context, i.e. the specification of big data solutions that buyers have to their suppliers. The results of this study could be applied to improve efficiency of information exchanges in big-data related activities, and the strategies raised provide multiple perspectives (buyer, supplier and the relationship between buyer and supplier) for the data services in Sweden to ensure a more nuanced view.

Last, the rest of the thesis is structured into five parts: literature review and conceptual model, methodology, empirical analysis, discussion, and conclusion. In section 2, previous research on buyer-supplier relationships governance and nudging is presented as well as the conceptual model that will be used to answer the research question. In section 3, the methodology is explained, with regards to research strategy and design, data collection and data analysis. In section 4, empirical findings will be presented and analyzed. In section 5, the main findings will be discussed and related to previous research. Lastly, in section 6, conclusions, limitations, and further research suggestions are presented.

2. Literature review and conceptual framework

In this section, our literature review and the conceptual framework will be presented. Section 2.1 includes a brief introduction on buyer-supplier relationships and uncertainty and biases in such relationships. Section 2.2. elaborates on strategies to manage uncertainty and biases. Last, section 2.3 elaborates on the conceptual framework that will be used to analyze the empirical material.

2.1 Background on the buyer-supplier relationship

Research says that buyer-supplier relationships are cooperative long-term relationships with the aim to improve operational performance, i.e. cost savings and quality, of both buyer and supplier (Vanpoucke et al., 2014, Monczka et al., 1998). The buyer-supplier relationship extends beyond traditional buy-sell arrangements as there is interdependence between parties, mutual benefits of the parties, and continuous, joint participation in areas such as technology (Yoshino and Rangan, 1995). Van de Ven (1994) defines the relationship between buyer and supplier as a "*repetitive cycle of negotiation, commitment, and execution*."

It is established in research that buyers and suppliers build partnerships to gain competitive advantage. Research argues further that buyers and suppliers collaborate and exchange technical capabilities with one another in order to enhance quality and innovation capabilities (Mohr and Spekman, 1994). Examples of such initiatives are technical assistance, information sharing and training to expand the buyer's knowledge base (Zajac and Olsen, 1993). Moreover,

research argues that buyers and suppliers combine and exchange knowledge (Vanpoucke et al., 2014) through governance mechanisms to lower transaction costs and allow realization of relational rents (Dyer and Singh, 1998, p. 662). More specifically, knowledge exchange between buyer and supplier is the sharing of information to resolve problems, with the aim to align goals and find opportunities of joint value creation (Palmatier et al., 2013). Such information sharing could be capabilities on how to manage data. While previous research has focused on data management in public-private relationships (Aben et al., 2021), research on relationships with two private actors where focus is on the sharing of capabilities to manage large volumes of data is limited. The next section will review previous studies on how lack of digital capabilities affects the buyer-supplier relationship.

2.1.1 Uncertainty in the buyer-supplier relationship

In the buyer-supplier relationship there is a lack of information. Research defines this phenomenon as environmental uncertainty and more specifically as "*the difference in amount of information needed and the information already acquired by the organization*" (Galbraith, 1973, p. 5). Studies have investigated uncertainty in buyer-supplier relationships of ICT services (van der Valk and Rozemeijer, 2009). Uncertainty in buyer-supplier relationships identified in research may be that the buyer has little knowledge about the capabilities and resources of suppliers and the supplier has little knowledge about the needs of the buyer. In-depth case studies to fully capture complexity of the knowledge exchange in buyer-supplier relationships are limited (Kohtamäki and Partanen, 2016). Further, there is increased research on data-driven decision-making and the opportunity for big data to contribute to valuable business insights and improved decision-making in organizations where machines collect and transform large volumes of data (Sivarajah, 2016). Implementation of processes that are data-driven and software-managed entail uncertainty with regards to data, as the buyer does not know which data is required and how it should be transformed successfully (Abet et al., 2021). As firms move towards data-driven decision-making, there is a need to gather correct data, structure it and transform it into valuable business insights. Aben et al. (2021) talks about two types of challenges in buyer-supplier relationships: uncertainty (lack of information) and equivocality (ambiguity of information). Lack of information can be mitigated through data acquisition and ambiguity of information through data transformation, i.e. presenting the data in a logical way. The study argues further that despite companies going through digital transformation through increased use of digital technologies there is scarce research done on how buyer-supplier relationships collect and transform data together. Also, future research should investigate relationships where there is alignment on economic value creation, such as private-private relationships, in more detail (Aben et al., 2021).

2.1.2 Biases in the buyer-supplier relationship

Buyers and suppliers make decisions based on information accessible in their relationships. Also, decision-makers are subject to cognitive biases that hinder them from objectively evaluating information (Beshears and Gino, 2016). One such bias is excessive optimism, where the decision maker is *"overly optimistic about the outcome of the planned action."* This bias steers the decision maker into overestimating the probability of positive events and

underestimating that of negative events. Another bias is overconfidence. Due to this bias, the decision maker overestimates their relative skill level and consequently the ability to affect future outcomes. A third bias is anchoring and insufficient adjustment. This is when the decision maker roots their decision in one initial value and is then not able to think beyond that value. Moving on, Simon (1955) defines bounded rationality as when the decision maker faces incomplete or intractable information, and where solutions made by the decision maker are adequate instead of optimal. The tendency to choose adequate solutions entail systematic irrational decision making. Systematic deviations from rational decision making are predictable cognitive biases (Thaler and Sunstein, 2009). Further, cognitive biases are possible to manage given the assumption that there is a difference between "Econs" and "Humans", where humans are social subjects that are influenced by others (Thaler and Sunstein, 2009). When choosing to purchase a service from a supplier, the buyer is facing incomplete information. There are studies that argue that buyers face incomplete information when developing the service specification that is provided to the supplier in the beginning of the relationship. The specification of the service entails incomplete information for the buyer, as the buyer neither has recognition of own needs in advance nor the expert knowledge to specify the service needed up-front (van der Valk and Rozemeijer, 2009). There are also studies that focus specifically on the specification of services for which the specification cannot be fully determined in advance and must therefore be developed together with the supplier as the supplier has an information advantage through their skills and expertise (Gelderman et al., 2015). Incomplete information in the specification may hinder the buyer from objectively evaluating decisions, which could result in cognitive biases in the buyer-supplier relationship. Along with previous research on uncertainty in data management mentioned above, the next section will introduce previous research on how uncertainty and biases can be managed in the relationship.

2.2 Strategies to manage uncertainty and biases

Buyer-supplier relationships depend on control and coordination to efficiently collect and transform data, which is managed through contractual and relational governance (Aben et al., 2021). There is increasing attention to studying contractual and relational governance (Selviaridis and van der Valk, 2019). Research explains governance between buyer and supplier using transaction cost economics (Heinis et al, 2022) as there are transaction costs incurred from the buyer-supplier relationship (Williamson, 1996). Transaction costs are costs such as costs associated with preparing contracts, negotiation costs and renegotiation costs due to changes in conditions. These costs should not be high enough that buyers may choose to vertically integrate. Transactions costs exist due to three characteristics that challenge the buyer-supplier relationship: asset specificity, uncertainty, and frequency. Uncertainty challenges the exchange between buyer and supplier due to an inability to predict events. Research argues that choosing the appropriate governance mechanism is necessary for efficient buyer-supplier relationships, in order to efficiently manage transaction costs that arise from uncertainty, to achieve fulfillment of joint objectives (Ketokivi and Mahoney, 2020), and to safeguard against opportunism (Poppo and Zenger, 2002). In short, transaction cost economics helps understand how uncertainty in buyer-supplier relationships can be mitigated by contractual governance (Williamson, 1996). There are both contractual and relational forms of

governance (Cao and Lumineau, 2015; Poppo and Zenger, 2002). Relational view theory argues that governance occurs through developing a relationship with the other party, i.e. relational governance (Cao and Lumineau, 2015; Dyer and Singh, 1998). Studies argue that uncertainty is derived from challenges regarding data collection and data transformation which in turn leads to the need to govern buyer-supplier relationships (Aben et al., 2021). The next section reviews what previous studies have shown regarding how contractual and relational governance are used to manage uncertainty.

2.2.1 Contractual and relational governance to manage uncertainty

Contractual and relational governance explain how suppliers and buyers efficiently manage data acquisition and data transformation. The idea is to safeguard against problems that arise due to unforeseeable changes (Poppo and Zenger, 2002). Contractual and relational governance may act as frames to mitigate information uncertainty that arise with regards to data acquisition and data transformation in buyer-supplier relationships (Aben et al., 2021, Lumineau, 2017).

To start, contractual governance is used through explicit documents that specify partner roles and obligations to provide future actions, with the aim to prevent disputes (Um and Oh, 2020; Poppo and Zenger, 2002). A contract may include arrangements on co-production between buyer and supplier (Ketokivi and Mahoney, 2020). Contractual governance specifies duration and completeness of the contract (Artz and Norman, 2002). Contract completeness regards the extent to which obligations throughout the exchange between buyer and supplier are defined upfront. Price, delivery, quality and terms and conditions contribute to completeness. In a complete contract such specifics are prescribed along with contract duration and detailed expectations of performance. This reduces the risk of opportunism, as contract terms are not renegotiable. However, the more time spent on trying to foresee contingencies in advance the higher the ex-ante negotiation costs. There may be characteristics of the service specification that cannot be determined at this stage, and such changes might occur after the contract has ended. Accordingly, incomplete contracts simpy line out general terms for price and quality and are less costly in terms of ex ante negotiation costs. While more room is left for flexibility and potential changes in the contract, there is instead the risk of opportunistic behavior and ex post negotiations costs. Accordingly, there is a trade-off between safety and predictability from a complete contract, compared to more flexibility from an incomplete contract (Poppo and Zenger, 2002). Moving on, Gelderman et al. (2015) argue that a buyer can face problems caused by uncertainty, as the supplier is more knowledgeable about the service provided through their skill or expertise. Gelderman et al. (2015) argue further contractual controls, e.g. splitting up large projects into smaller projects, can mitigate such an uncertainty.

On the other hand, relational governance manages uncertainty through social processes. Obligations occur through the development of social relationships to enable solidarity, flexibility, and information exchange. Solidarity and information sharing facilitate mutual problem solving, while flexibility enables adaptation when there are unforeseeable changes. Accordingly, cooperation and adaptation enable flexibility to manage uncertainty that arise in an exchange (Poppo and Zenger, 2002). Moreover, relational governance is connected to trust,

which improves performance of buyer-supplier relationships (Paolucci et al., 2021; Poppo and Zenger, 2002). Relational governance is based on norms, which are the expectations on behavior and trust in the other party's benevolence and credibility. Also, in procurement of complex services, contracts are per definition incomplete, resulting in trusting relationships as adjustments are required after the contract is signed (Heinis et al., 2022). Further, studies say that relational governance should be used when it is difficult to specify product features in advance (Paolucci et al., 2021). Gelderman et al. (2015) argue that consulting services are based on knowledge and expertise of professionals who can diagnose the problem and formulate goals. More specifically, buyers need to be educated by service providers on what can be achieved from the purchase. On the other hand, the supplier needs to understand the buyer's business processes in order to offer the best solution (van der Valk and Rozemeijer, 2009). Further, there are two dimensions of relational governance, i.e. structural and process. The process dimension is associated with expected and realized activities that are necessary for joint problem solving and sharing of information. Moving on, Aben et al. (2021) argue that buyer-supplier relationships require governance mechanisms to efficiently mitigate uncertainty derived from data acquisition and data transformation. Also, this study argues that there are limited insights on how contractual and relational governance could be used to efficiently manage data acquisition and data transformation.

2.2.2 The interplay between contractual and relational governance

Research argues that contractual and relational governance may work as substitutes to one another in buyer-supplier relationships (Poppo and Zenger, 2002). For instance, there is research suggesting that trust reduces transaction costs and facilitates adaptation without the need of a formal contract (Larson, 1992:98). Even so, there are researchers that claim that formal contracts might actually affect cooperation negatively (Moran and Ghoshal, 1996). Furthermore, there are studies that argue that contract design has a negative impact on trust, but such research would require further empirical validation (Lumineau, 2017). In brief, researchers that argue that contractual and relational governance mechanisms are substitutes argue that only one is used in a buyer-supplier relationship.

Poppo and Zenger (2002) also argue that contractual and relational governance may work as complements. The combination of clear contractual terms together with relational norms such as solidarity and flexibility may induce cooperation. The formal contract reduces short-term gains while ensuring that there are expectations of cooperative behavior. Accordingly, formal contracts can act as a complement to informal cooperative behavior, i.e. relational governance (Baker et al., 2022; Larson, 1992). On the other hand, there are situations where some dimensions might be difficult to specify in a contract, e.g. unforeseen contingencies, where relational governance can ensure an attitude of mutual adaptation. Nevertheless, relational governance acts as a complement to formal contracts as a method to adapt to changed circumstances and provide stability. In complex buyer-supplier exchanges, the contract is not complete when signing, which entails a need for relational governance e.g. shared norms and values, which can provide flexibility in the procurement process, e.g. share interpretations, renegotiate and make adjustments (Poppo and Zenger, 2002). Relational governance enables

dense social ties, which may prevent buyer-supplier relationships from discovering new opportunities. Accordingly, relational governance should only be invested in if there is high information uncertainty (Paolucci et al., 2021). In short, contractual and relational governance may complement each other.

To conclude, there is research studying in which situations contractual and relational governance act as complements or substitutes (Cao and Lumineau, 2015; Poppo and Zenger, 2002). However, research is conflicted on whether governance mechanisms act as complements or substitutes (Um and Oh, 2020).

2.2.3 Contrasting buyer and supplier governance arrangements

Buyer and suppliers may use governance mechanisms differently. Most previous studies have focused on only one of the partners, mostly the buyer, and few studies have accounted for both buyers and suppliers by incorporating both perspectives into one model. At the same time, there is increasing importance of such studies, as buyers and suppliers have different priorities. For example, buyers value trust higher than suppliers (Um and Oh, 2020).

Studies argue that buyers aim to write contracts that outline roles and responsibilities of the supplier as well as incentives and punishment. By using contractual governance, the buyer can manage the relationship with their supplier by coordinating tasks and controlling opportunistic behaviors. On the other hand, buyers may use relational governance for negotiation and engaging in a long-term relationship. Also, buyers may engage in information exchange with their supplier by sharing core knowledge (Um and Oh, 2020). Nevertheless, high levels of uncertainty makes contracting expensive and more complex, which results in high transaction costs. This can lead to buyers choosing vertical integration or short-term exchange (Poppo and Zenger, 2002). Nevertheless, formal contracts ensure that the initial stages of an exchange are successful (Larson, 1992), which is beneficial for buyers who have not specified their need in advance. In brief, research argues that buyers tend to use contractual and relational governance as complements.

Research states that suppliers may be more inclined to use contractual governance exclusively and as a result may be less engaged in providing innovative solutions to safeguard themselves against unequal gains (Um and Oh, 2020). In order to engage in supplier-initiated activities completeness of contracts is required (Selviaridis and van der Valk, 2019). On the other hand, relational governance may be used by suppliers if there is a high degree of trust in the relationship. However, as the use of an extensive contract may have a negative impact on trust, one or the other may be used by suppliers. In short, suppliers tend to use contractual and relational governance as substitutes. Overall, research is conflicted on the use of governance mechanisms as substitutes or complements as most studies have focused on the buyer perspective (Um and Oh, 2020).

2.2.4 Contractual and relational governance joint impact on performance

Research is conflicted regarding the impact of governance on performance (Cao and Lumineau, 2015). There are studies on collaborative buyer-supplier relationships (Um and Oh, 2020) that result in efficiency and transaction cost advantage for the buyer (Um and Kim, 2019). Further, Kohtamäki and Partanen (2016) argue that asymmetries in the relationship require buyers and suppliers to create value together. Further, they argue that value is created in the continuous interactions between supplier and buyer resulting in relationship learning. The continuous interaction is the foundation for the development of customized solutions that will satisfy the needs of the buyers. Wang et al. (2008) argue that governance mechanisms enable safeguards that facilitate generation of creative ways of dealing with business activities in buyer-seller relationships with the result of improved knowledge-sharing routines. Other studies have established that there is a positive role of value co-creation on sales performance (Kohtamäki and Partanen, 2016). Last, Heinis et al. (2022) state that the value co-creation process is an important feature of services, where information sharing and transparency are prerequisites for success.

2.2.5 Nudging to manage biases

Research has flourished on how to manage cognitive biases to enable improved decision making (Congiu and Moscati, 2022). Research argues that the decision maker is subject to cognitive biases that affect the decision maker to make decisions that they could have avoided if they had complete information (Battaglio et al., 2019). Nudging is a new and emerging research field that aims to explain how to manage cognitive biases (Congiu and Moscati, 2022). Thaler and Sunstein (2009) have contributed extensively to nudging literature. Thaler and Sunstein (2009, p. 6, 8) define a nudge as "any aspect of the choice architecture that alters people's behavior in a predictable way without (1) forbidding options or (2) significantly changing economic incentives. The nudge should also significantly alter the behavior of the decision maker. A nudge should not reduce the set of choices that the decision-maker is facing, but there could be additions to the choice set. In short, an example of a nudge is a so-called decoy (Congiu and Moscati, 2022). By providing a dominated option the decision-maker can be steered into a predictable direction without other options being forbidden. A decision-maker should not be forced to comply with the nudge, leaving room to accept the nudge or not. Further, a nudge is also defined as "private initiatives that steer people in particular directions but also allow them to go their own way" (Sunstein, 2018, p. 61). For example, educational campaigns convey factual information without compromising the liberty and autonomy of the individual (Congiu and Moscati, 2022). Another example of nudging in B2B exchanges is when suppliers nudge buyers into quicker and cheaper data management by using certain technological tools when working with them in order to facilitate the format of the data (Clancy, 2000).

Moving on, the decision maker benefits from the nudge if the decision that must be made is rare and/or difficult, where they will not receive instant feedback, or when the situation cannot be easily understood. Such a decision could be far away in the future and difficult to picture (Battaglio et al., 2019). Further, rationalization of choices through nudging assumes that the decision-maker has "true" preferences if they had complete information (Thaler and Sunstein,

2009). Further, when it comes to commercial nudges, a win-win transaction where both supplier and buyer are satisfied should be achieved. Nudges should steer choices so that the decision-maker could make a decision as if they were rational and/or had complete information (Thaler and Sunstein, 2009). Last, suppliers may nudge buyers to prevent certain purchases. There is a study on nudging to prevent purchases of products that are incompatible to the users' devices or operating systems with the aim to manage disappointment. The study showed that nudging mechanisms such as warning messages and information placement at a certain stage in the purchase process had a significant effect on purchase (Esposito et al., 2017).

2.2.6 Research gap

Many studies on buyer-supplier relationships have investigated, although with conflicting results, governance arrangements where contractual and relational governance are used as complements or substitutes. Less focus has been put on governance arrangements of specific relationships with a successful outcome. One such relationship that has barely been studied is private-private relationships where buyer and supplier manage large volumes of data in their relationship. No studies have exclusively focused on relationships where suppliers offer buyers help with data acquisition and data transformation and how such relationships are managed through contractual and relational governance. Further, there is an imbalanced view in the governance literature regarding buyer and supplier perspective, as most previous studies on governance mechanisms have focused on the buyer perspective. Also, there are few studies that have incorporated both studies into one model. Moving on, it is established in previous research that the specification of a service is subject to incomplete information for the buyer. However, to our notion there are no studies that have explored that the specification of a service may result in cognitive biases for the buyer when starting a relationship with their supplier. In short, the research gap identified is governance of private-private relationships in the context of data acquisition and data transformation and nudging to manage high expectations of a service. By including buyer and supplier perspectives into one conceptual model, the aim is to explore the use of governance mechanisms as complements and substitutes to improve the success rate of big data solutions. Also, this study explores how suppliers manage high expectations from buyers with regards to the specification of the big data solution that the buyer has towards the supplier by using nudging.

2.3 Conceptual framework

We will analyze the empirical material using theory on nudging (Thaler and Sunstein, 2009) and governance mechanisms (Williamson, 1996; Dyer and Singh, 1998).

First, the buyer is subject to incomplete information when defining the specification of the service to the supplier (van der Valk and Rozemeijer, 2009; Gelderman et al, 2015). Incomplete information results in bounded rationality (Simon, 1955), which may lead to cognitive biases as buyers are excessively optimistic about the probability of a positive outcome (Beshears and Gino, 2016). Suppliers can manage such cognitive biases through nudging, steering choices so that the buyers could make decisions as if they were rational and/or had complete information (Thaler and Sunstein, 2009). Nudging may be used to prevent incompatible purchases.

Examples of such nudges are warning messages and information placement (Esposito et al., 2017).

Second, the buyer is subject to uncertainty (Galbraith, 1973, p.5) as there is a difference between the information needed and already acquired by the organization, resulting in an asymmetry between the buyer's current situation and the ideal situation. The supplier has data capabilities to mitigate this uncertainty through data acquisition and data transformation together with the buyer (Aben et al., 2021). Data acquisition is when the supplier helps the buyer acquire data, and data transformation is when the supplier helps the buyer transform data into valuable insights or automate processes. Uncertainty creates transaction costs (Williamson, 1996) and governance mechanisms may be used to manage transaction costs and allow realization of relational rents (Dyer and Singh, 1998, p. 662). Uncertainty may come with unforeseen contingencies that can be safeguarded against through contractual governance (Williamson, 1996). Contractual governance highlights predetermined duration and completeness of the contract in terms of price and delivery (Artz and Norman, 2002). Contractual governance may be used in the beginning of the relationship as the formal contract could safeguard towards uncertainty during the initial stages (Larson, 1992). Moreover, contractual governance includes splitting up large projects into smaller projects (Gelderman et al., 2015). On the other hand, relational governance occurs through the development of social relationships to enable solidarity, flexibility, trust, and information exchange (Poppo and Zenger, 2002). Solidarity enables mutual problem solving and flexibility enables adaptation when there are unforeseeable changes (Poppo and Zenger, 2002). Trust may be used when it is difficult to predetermine what should be delivered in advance (Paolucci et al., 2021). Information exchange may be through sharing of core knowledge (Gelderman 2015, Um and Uh, 2020). Relational governance should be invested in when there is high uncertainty (Paolucci, 2021). Moving on, contractual and relational governance may be used as complements, where the combination of clear contractual terms together with relational norms such as solidarity and flexibility induces cooperation (Poppo and Zenger, 2002). On the other hand, contractual and relational governance may be used as substitutes when contract design and trust affect each other negatively (Lumineau, 2017). Buyers tend to use contractual and relational governance as complements while suppliers tend to use contractual and relational governance as substitutes (Um and Uh, 2020). Below is an overview of the theoretical framework that will be used.

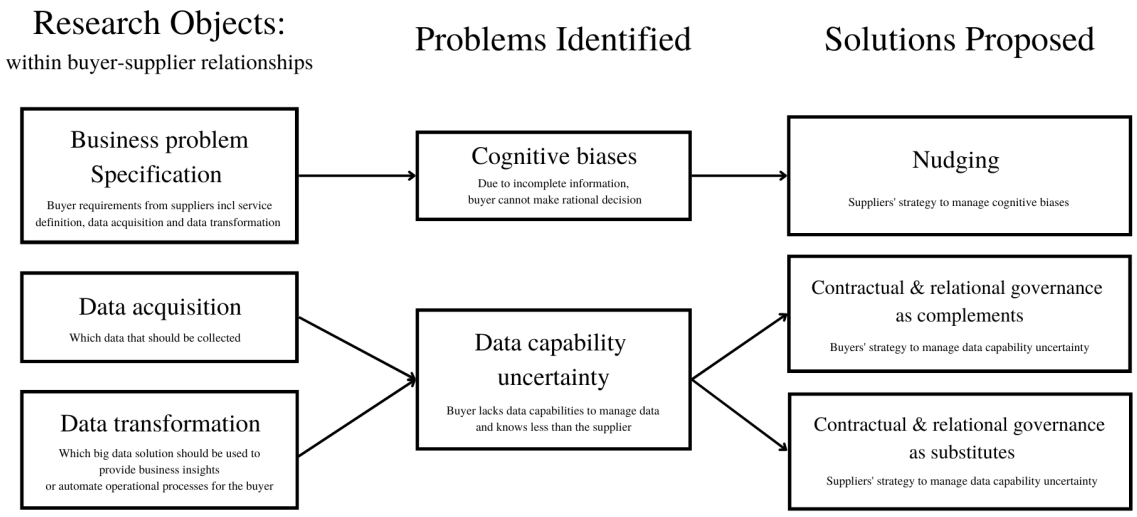


Figure 1. Conceptual framework

3. Methodology

3.1 Research approach

3.1.1 Research strategy

We used the interpretative paradigm to conduct this study. The aim was to explore buyer-supplier relationships of big data solutions and more specifically how they managed data together. We noticed that the buyers and suppliers had different understandings of their relationships, implying that there is no objective reality. Rather, a social reality emerges in such relationships, which we wanted to explore through our own theoretical interpretations. In interpretivist research the assumption is that reality is socially constructed, where theory and empirics are iterated throughout the study (Eisenhardt, 2021). Our view of theory has been to interpret and understand constructs in our empirics and how they were linked together. These constructs have then been interpreted as theoretical concepts and mechanisms to explain how the constructs are linked together theoretically. For example, we realized in our empirics that efficient data management could not be explained by certain theoretical concepts, i.e. negotiation (Geiger, 2017), as the interviewees did not perceive data capability uncertainty to be managed through negotiation, but required other theoretical concepts and mechanisms to fully understand the relationships i.e. governance. Further, while the aim was to use governance (Poppo and Zenger, 2002) as our main theoretical concept to interpret our data, nudging (Thaler and Sunstein, 2009) was also identified in our empirics. Nevertheless, we have interpreted the empirical data through a dialogical process with theory, and our subjective interpretations were used to conduct the study and reinforced through our social reality (Bell et al., 2019, p. 24). Moreover, we asked exploratory questions on how the buyers and suppliers worked together to manage efficient data management. In order to understand how challenges with data

acquisition and data transformation were solved through governance and nudging, a qualitative study was suitable (Eisenhardt, 1989).

3.1.2 Research design

This study explored how to manage data capabilities uncertainty and cognitive biases in buyer-supplier relationships of big data solutions. This was most easily done by conducting a multiple case study using the Eisenhardt method (1989). We thought this method was suitable as it aims to address research questions where prior research has conflicting theoretical implications and/or little empirical evidence (Eisenhart, 2021). Governance mechanisms as complements or substitutes is an area of research which is conflicting (Um and Uh, 2020). Further, data acquisition and data transformation in buyer-supplier relationships has little empirical validation (Aben et al., 2021). Also, this method goes hand in hand with addressing research questions that aim to answer under-represented perspectives (Eisenhardht, 2021). We thought this notion applied to our case, as we wanted to explore the supplier perspective further, which is much less researched compared to the buyer perspective (Um and Oh, 2020). Further, Eisenhardt (2021) emphasizes careful case selection through theoretical sampling based on several criteria. We wanted relationships where historical data was incomplete and/ or ambiguous and where the suppliers would help buyers to manage their real-time data (Aben et al., 2021). We saw buyer-supplier relationships of data consultancy and software services as cases where such data management was likely to occur. We limited ourselves to Swedish companies based on availability.

Scope and sampling

Initially, we wanted to focus on logistics cases, i.e. suppliers offering big data solutions for logistics operations as we found this to be an interesting phenomenon. However, due to lack of data availability we had to widen our scope to big data solutions for buyers within various industries as well as suppliers offering more than software within logistics to suppliers that delivered data-science consultancy, research-oriented data science consulting and software-as-a-service within various industries. This is in line with Ligita et al. (2020) that argues that theoretical sampling may include expansion of research settings. We searched for suppliers by looking at websites of different suppliers and eliminated those that were leaning towards strategy consulting within big data solutions as that would imply more consulting on how to develop a digital strategy and less focus on data management. By focusing on data management as the common denominator, we aspired to achieve generalizability. For instance, the buyers to our suppliers were active in various industries (i.e. software, pharmaceuticals, metal manufacturing, water solutions manufacturing and fashion) and were subject to data acquisition and data transformation activities. Further, a common process design was used (Eisenhardt, 2021) where the same phenomenon, buyer-supplier relationships of big data solutions, was studied in different settings, i.e. industries, but with the same process and outcome, i.e. efficient data management. However, as we wanted to put more emphasis on the supplier perspective, less efficient cases were also explored in our data, which entailed more of a polar hybrid design (Eisenhardt, 2021). This enabled us to capture a more nuanced view of what buyers needed help with that was not covered by the buyers that we interviewed.

Due to availability, the design was also based on snowball sampling (Bell et al., 2019, p. 395). When we had interviewed a supplier, we would ask them if they could give us contact details to a buyer. However, we managed to reach out to most buyers on our own. As suppliers had published cases on their website, we managed to find buyers that way. We made sure to select buyers that had recently been working with their suppliers so that they would more easily remember details and important events from the relationship. The issue with availability directed our data collection to some extent. Moreover, we chose to move away from AI procurement to buyer-supplier relationships of big data solutions as we shifted focus from procurement behavior to data management. We realized along the way that the procurement process in itself was not necessarily different from that of other services, but rather the role of the supplier in the relationship. Further, we noticed in the data that there were different ideas of AI and thus there was a discrepancy between buyers and suppliers in terms of whether AI was procured or not in the relationships. Thus, we chose to redefine from AI to big data solutions to widen the scope of supplier offerings.

Last, the representatives on the supply side were CEO:s, while the representatives on the buy side were CEO:s, CTO, COO, head of R&D and head of development. As we chose the unit of analysis to be the relationship between buyer and supplier, we found it relevant to interview people with the highest seniority level possible to fully be able to capture this level of analysis. Also, we made sure that we interviewed people that actively engaged in the relationship with the other party, i.e. participated in the procurement process. Company size for buyers and suppliers varied from sales 2021 of 7M-2B. A list of interviewees is to be found in appendix 1.

3.2 Data collection

The empirical observations in this study were interviews with suppliers and buyers of big data solutions. We did a pilot interview with a supplier that was developing a big data solution for logistics cases. This interview was insightful as we could better understand the different big data solutions offerings on the market, which guided us on how to define our sample characteristics. Next, 12 people were interviewed during September, October, and November 2022. We reached out to suppliers by finding their websites. In order to increase our data collection, we asked some suppliers for contact details to their buyers, but they were reluctant to share contact details due to NDA. However, as we found buyers on supplier websites, we still managed to interview buyers as well. Most suppliers responded and accepted interviews, while some buyers did not respond or declined the offer because of time constraints. Before meeting with the buyers, we read up on the cases as an additional data source.

Interviews were semi-structured to allow for an open discussion (Bell et al., 2019, p. 436). The average length of the interviews was 40 minutes, and all interviews were video interviews as buyers or suppliers were either located in other cities or found it more convenient to do so. The interview guide used may be found in appendix 2. In the beginning of each interview, we explained the purpose of the study, granted anonymity regarding company names and personal names, and asked for consent to record the interviews and informed them that we would ask if

we wanted to use quotes, which all interviewees accepted. We also confirmed all the quotes used for the analysis with the interviewees afterwards through email.

As the interviewees were told that our focus was on AI they answered accordingly. Thus, in our interview data the interviewees use the word AI rather than big data solutions. However, AI is tightly connected to big data and more specifically AI is defined as a system's ability to interpret and learn from external data and use such learnings from data to achieve goals. More specifically, AI obtains external information from big data sources (Kaplan and Haenlein, 2020). Thus, we argue that the words AI and big data solutions may be used interchangeably.

Last, one of the last interviews we made, with S6, was excluded from our sample as they were supplier-driven and offered one specialized solution, which eliminated most of the challenges we identified in the other cases. Thus, quotes from S6 were not used in the empirical analysis.

3.3 Data analysis

An inductive approach was used to conduct our multiple case study, as we let the empirical data build our conceptual model. Initially, we wanted to base our conceptual model on negotiation literature. However, after initial analysis of the first interviews we realized that the interviewees explained relationship governance. The interview guide had to be adjusted accordingly. We revised our interview guide by improving our questions after initial data collection, which is in line with theoretical sampling with regards to improving interview questions to better capture gaps in the data (Ligita et al., 2020).

Moreover, the research question had to be revised as we worked through the empirical analysis. Initially, our research question was: *How are business negotiations managed in AI procurement for start-ups and medium-sized companies?* However, we moved away from negotiations in the procurement process as we realized that they were simple and straight-forward and instead decided to focus on how they managed the relationship through governance. After having analyzed most of our empirical material, we realized that an additional theoretical lens, i.e. nudging theory, needed to be added for us to finish the empirical analysis. In brief, we let the empirical material form our theoretical framework (Eisenhardt, 1989).

We transcribed and coded all interviews individually in parallel to conducting more interviews. Then, the data was thematically analyzed by grouping codes and citations into themes (Eisenhardt, 1989). By conducting such analysis, we matched our inductive approach as theory and data was iterated throughout the whole study and findings were analyzed across cases (Eisenhardt, 1989). A coding table with examples of themes may be found in appendix 3.

3.4 Discussion of methodology

In line with Lincoln and Guba (1985), criteria to evaluate qualitative research have been used. First, we considered the credibility of our study. We read about the cases that the suppliers had available on their websites as an additional source to confirm what the buyers said in their interviews regarding data capabilities uncertainty, data acquisition and data transformation. By

reading up on the cases before each buyer interview, some degree of data source triangulation was achieved (Bell et al., 2019, p. 364). Second, with regards to transferability, we aimed to increase generalizability by identifying patterns across cases. This was illustrated by the fact that buyers were active in various industries but still faced similar challenges. Nevertheless, as we interviewed relatively few cases, the extent of external validity is still limited. However, thick description was achieved through detailed data presentation (Bell et al., 2019, p. 365). Third, regarding dependability, we did the first-order coding and second-order coding separately before joint discussion, to achieve inter-coder reliability (Aben et al., 2021). Last, confirmability was achieved as we were not inclined to use certain theories to analyze our empirics or let our personal values skew our findings (Bell et al., 2019, p. 365).

4. Empirical analysis

This section will display our findings from the 12 interviews conducted and is structured to contrast the perspective of big data solution buyers and suppliers.

4.1 Overview of the big data solution buyer-supplier relationships

In total there were 5 suppliers and 7 buyers interviewed. The buyers wanted help from their respective suppliers either to improve offerings towards their customers, to provide internal insights for the organizations or automate processes through machine learning. The relationships varied in data maturity. In some relationships, buyers wanted to explore their data together with the supplier, and as a result the big data solution project took longer and involved more interaction. In some of the relationships the buyers saw their supplier as a tool to transform their data with relatively short and simple interaction.

Supplier	***Company category***	***Big data solution offering***	***Corresponding buyers***
S1	Big data solution consultancy	Data management	B1, B2, B4
S2	Big data solution software service	Machine learning	B3
S3	Big data solution consultancy/research	Data management	B5
S4	Big data solution consultancy/software service	Data management/machine learning	B7
S5	Big data solution consultancy	Data management	B6

Table 1. Overview of the big data solution buyer-supplier relationships

In total, there were insights from 7 buyer-supplier relationships and additional insights from the suppliers about buyer-supplier relationships in general. Three gaps were identified in the interviews that prevented buyers from successfully procuring big data solutions: a motivation bias, a data capabilities uncertainty, and a digital ecosystem uncertainty. The motivation bias was that buyers had high expectations of big data solutions. The data capabilities uncertainty

was that buyers lacked data capabilities required to procure a big data solution. The uncertainty constituted two types: (1) the buyers did not have capabilities to collect data (2) the buyers did not have capabilities to transform data into business insights or to automate business processes. Last, the digital ecosystem uncertainty refers to that the buyers are generally undeveloped in the continuous digital transformation progress, involving the unadaptable employees and unmatched operational structures.

4.2 Motivation bias

The buyers in the relationships were subject to cognitive biases, as they were overly optimistic about supplier capabilities to offer successful big data solutions. This was identified when they defined their business problems in their specification to the suppliers (Beshears and Gino, 2016). The suppliers addressed that in their relationships with buyers there were high expectations, meaning that the specification included solutions that exceeded what was feasible for the suppliers to offer. The suppliers addressed this as a gap with buyers in general and not specifically with the buyers interviewed. The gap was a result of incomplete information (Thaler and Sunstein, 2009). The buyers interviewed had some information, varying from little to complete, required to specify to their suppliers how big data solutions could solve their business problem.

4.2.1 Overly optimistic expectations

Suppliers talked about that buyers had too high expectations about which big data solutions could be provided. To start, S1 argued that high expectations affects whether the relationship will result in successful data management or failure: "*One big reason (for failure) is that I see so many AI projects that have a technical focus and so they sort of forget that AI is just a tool that is supposed to solve a problem"*. S2 argued that high expectations was a recurring issue: "*Sometimes it happens that they think it would do more than it does, so that can definitely be a problem, like they had higher expectations of what AI could do"*. S2 exemplified such expectations by saying that buyers thought that the big data solution could be applied to a larger scope than what was feasible: *"Someone would say something like, can it configure my whole system?"*. S3 said that buyers read about big data solutions and think that such solutions are applicable to their organizations:

> *"The expectations of AI are far out. Generally, people have too high expectations about AI from looking at what is reported in social media. Like well, I read that AI can do this, can't we do that in our company?"*

Further, expectations were mentioned by S5 as a challenge: *"A challenge for them because often they have heard about something cool that you can use AI for, and they want to do that."* S4 argued that expectations were an important part of an efficient buyer-supplier relationship: *"Customer expectations are really really important when having a successful project"*. In brief, it was identified that S1, S2, S3, S4 and S5 thought that buyers had high expectations with regards to what big data solutions could do to solve business problems or automate processes.

The strategy identified to manage high expectations was to set the bar low from the beginning. S2, S4 and S5 exemplified this strategy. S2 explained that a strategy they used to manage high expectations was to tell buyers from the beginning what the limitations were: "*So just telling them as early as possible is pretty much our strategy now. Like try to get them done quite early, like it (big data solution) doesn't do this"*. S2 knew buyers might not have bought their solution if they knew from the beginning that it could not do more. S2 further explained the risk of promising too much to the buyer:

"Then they get very disappointed near the end when they're supposed to buy something. But if you say right away, we probably can't do that, and it has these limitations. Then when they get to the end, their expectations won't be super high."

Moreover, when dealing with the specification of the big data solution provided by the supplier it was important for suppliers to disclose information. This was highlighted by S4 when they explained to their buyers what big data solutions could do for them: "*You need to have a clear communication with the client, so you don't promise too much."* Last, S5 explained that clear communication was crucial for them when developing relationships with their buyers:

"We need to be more straightforward in our messaging, saying what we think and what we believe can be done and not be afraid that the customer will not want to work with us because promising too much is never a good idea."

The suppliers argued that buyers had too high expectations on what big data solutions could do. High expectations were identified in the specification that buyers had to the suppliers where they explained what they wanted help with. Accordingly, buyers have high expectations about the capabilities of suppliers (Gelderman et al., 2015). The buyers faced incomplete information (Simon, 1955), when entering relationships with suppliers and they thought that they would purchase a big data solution that can do more than what the suppliers would offer in the end. Accordingly, in line with Thaler and Sunstein (2009) buyers were subject to cognitive biases. The cognitive bias identified was excessive optimism (Beshears and Gino, 2016) as the buyers overestimated supplier capabilities to offer successful big data solutions and underestimated that of failure solutions. This was identified in how the suppliers understood the specification from buyers in the beginning of the relationship (van der Valk and Rozemeijer, 2009). To help buyers overcome excessive optimism, suppliers used nudging (Thaler and Sunstein, 2009), which was done by setting the bar low from the beginning. The buyers were influenced by suppliers as they were nudged towards choosing to buy big data solutions that were within a smaller scope than they initially thought. The suppliers were transparent with the limitations or were clear in their communication so that they were not promising too much. For this strategy, setting the bar low, the first nudge identified was through a "warning message" (Esposito et al., 2017). The suppliers were transparent with the fact that some big data solutions may not be compatible with the business problem they wanted to solve. The second nudge identified was through information placement towards buyers (Esposito et al., 2017). The suppliers told buyers as early as possible in the relationship rather than towards the end what big data

solutions they could offer to solve the business problems. The information was provided rather at the description stage of the relationship rather than at the payment stage.

4.2.2 Vague to clear specification to the supplier

Moving on, the buyers interviewed showed some degree of information required to provide a specification to their suppliers. The spectrum varied from some to complete information. First, there were buyers with specifications that were more vaguely defined in the beginning of their relationships. These buyers were B2, B4, and B5.

To start, B2:s specification entailed more of an explorative relationship with their supplier as they did have little information about supplier capabilities to solve their business problem. They did not know exactly what they would need and could not specify what data transformation S1 would be able to offer to them:

"*We have a fetish for numbers and analytics, and we think it's really interesting, intriguing and we are deeply interested in having some experience also working with the smart people in the AI field and discovering how that would look more in depth."*

Next, B4 wanted to "*try AI and get the company interested in this new technique"* but they could not provide an exact specification in advance towards their supplier. However, they provided a specification including the business process for which big data solutions could be used: *"We did a map of the process before we contacted AI companies."* Last, B5 explained that they saw an opportunity that would make their customer's daily operations much more efficient:

"*What we know quite clearly is that our customers spend a lot of resources and time sitting in cars, driving around to the different pump stations and making inspections regardless if it's needed or not. We see a quite clear possibility with new sensor technology and new communication solutions and data handling. We saw an opportunity or possibility to reduce the cost that customers have to drive around so that was quite clear."*

Next, some buyers had complete information and could fully specify what service they needed from their suppliers. These buyers were B1, B3, B6 and B7. To start, B1 had a clear idea about the initial problem when they approached S1, which was to improve the software they offered to their customers: *"We didn't go there with the idea that "can AI help us?". That wasn't the brief that we sent. We sent "this is the problem that we want to solve and can you help us solve it with these constraints"."* Next, B3 had a clearly defined goal for purchasing a big data solution from S2, which was to improve the application they provide to their end-users: "*So we were out like it's specifically in the X (company name) investor relations app, which is our service. We wanted the time stamping part which is AI taking all the texts and matching it with audio."* Accordingly, B3 knew which S2:s capabilities were and could specify what they wanted help with upfront. Moving on, B6 also showed that they had complete information regarding the specification when they explained that they knew what they wanted from S5:

"*I knew that they had the right kind of expertise for us. So I approached them and we had to talk about our expectations and deadlines for the initial project. They provided us with some resources and then we were on our way."*

Last, B7 also had a clear specification of the service towards S4:

"I had quite a clear idea on how I wanted to take this work forward. So my idea was that, besides getting a partner to help us out with this, I also wanted us to get the competence in house. So I wanted to do the training myself on becoming a robot developer alongside a colleague of mine from the IT department."

In brief, the suppliers explained that buyers in general had too high expectations on supplier capabilities to solve their business problems. The buyers interviewed either had little information or complete information regarding which big data solutions were feasible, which was reflected in the specification they provided to their suppliers. The buyers with less information when initiating a relationship with their supplier wanted to work with their suppliers in a more explorative manner (B2, B4, B5), while the buyers with complete information with regards to the data specification were more focused on the end goal (B1, B3, B6, B7), which mainly was to deliver an improved offering to the end-users.

4.3 Data capability uncertainty

The buyers did not have data capabilities to successfully procure big data solutions and were thus subject to an uncertainty (Galbraith, 1973, p.5) that could be mitigated through buyer-supplier interaction. The uncertainty consisted of two parts. The buyers (1) did not have capabilities required to collect data (2) did not have capabilities to transform data into business insights or automate business processes. These two types of uncertainty were mitigated by (1) data acquisition and (2) data transformation (Aben et al., 2021). The suppliers helped buyers with both data acquisition and data transformation or only data transformation. It was identified that data acquisition took place as the suppliers helped buyers with data collection as well as setting up the right infrastructure for data collection. On the other hand, data transformation took place as the suppliers helped buyers by using the buyers' data to train algorithms. Further, it was identified that contractual and relational governance were used as frames to enable efficient data acquisition and data transformation (Aben et al., 2021). The suppliers emphasized using contractual governance through splitting up projects into smaller parts, starting with the easiest project and staying within the scope of projects. The buyers emphasized using contractual governance by splitting up payments and relational governance by being transparent and communicative.

4.3.1 Data acquisition

One first empirical finding in this section was that the suppliers argued that buyers had an uncertainty when it came to data collection and infrastructure. This uncertainty had to be mitigated through data acquisition. S1 emphasized that this was the case for buyers in general:

"*I think maybe on a good day, 10 % of the companies are AI ready, but I think it's maybe just 5%. (...) They just don't have the data*". S4 argued that buyers need help with the infrastructure that is required to collect the right data: "*They cannot do AI data, they don't have any infrastructure for collecting data and building apps on top of them. If you don't have that infrastructure, then you need to build that first."* S4 explained further that having the right infrastructure enables companies to scale the big data solution within the organization: *"Let's say that you're gonna scale up from one day to another. One day you're gonna interpret 10,000 invoices and then the next interpret 30,000 or 300,000. Then you need the infrastructure to scale."* Nevertheless, it could also be the case that, if the right infrastructure was not in place, the buying company would systematically collect the wrong data. The suppliers explained that this was the case for many companies that wanted to procure big data solutions. This was exemplified by S3:

"*One obvious example is from public transportation, where currently all the transportation like X (customer), is planned in an old-fashioned manner where they use data from blips when we use the card and from questionnaires that are collected from people traveling. So the traffic is actually planned from the people that already use the public transportation quite a lot."*

S3 provided an example of a buyer that did not have the right infrastructure to collect data and thus faced an uncertainty as they did not have data capabilities to acquire data. As a result, successful data acquisition was not possible. Firstly, it was biased: *"It's a huge bias because there's no data from people using cars entering the planning of public transportation".* Secondly, due to the infrastructure, only historical data could be acquired, while big data solutions require real time data collection as well:

"If you do a questionnaire and then when you get data it is already a couple of months old. It's very expensive to do questionnaires. You should maybe do one per year. So it becomes a very non adaptive planning tool. While an AI solution for instance, how you build it, it is based on real time data."

S3 managed uncertainty by offering an easier project to the buyer instead, where data acquisition was feasible. The uncertainty would then be mitigated for a less complex project, while the other project remained as a research project:

"*So currently this kind of traffic planning topics are carried out in research projects financed by X (Swedish innovation authority). Far from being reality yet. The things we're doing with X (buyer) currently are the security cameras in the subway that detect if someone falls into the tracks or faints on the platform."*

In brief, suppliers argued that buyers in general did not have data capabilities to solve certain business problems. As a result such buyers did not have the right data or the infrastructure to collect the right data. Accordingly, buyers in general were subject to uncertainty (Galbraith,

1973, p.5). However, the suppliers did not see fit to engage in data acquisition for such projects, but chose to offer simpler projects instead.

Moving on, a second empirical finding was that all the buyers interviewed had the right infrastructure to collect data except for B4. In the relationship between B4 and S1, B4 needed help setting up an infrastructure to collect the right data. B4 explained that they first sat down together with S1 and discussed which data they should collect to solve the business problem. B4 shared important information about their operations to S1 as preparation for the first meeting:

"So it was a document of 4-5 pages where we can see different sensors in the machine that we could use if necessary and we had some data from universities before that, probably the raw material will react in case the humidity is higher or lower and the normal temperature is within these degrees."

The aim was to provide S1 with a deeper understanding of B4:s business processes that were related to the business problem, which was how to detect disruptions in B4:s manufacturing operations. At the beginning of the relationship, B4 did not have the data that was required for proper data collection. Accordingly, S1 helped them collect the data by deciding which data points were relevant for the business problem:

"For the first meeting, they (S1) had already received the map of our production and according to that they could already say from the first meeting that this is probably a very important part and we need to have the relationship between this sensor and the thermostat sensor also."

When this was established, B4 had to invest in sensors, i.e. the infrastructure that would collect the data, which would allow proper data collection in the manufacturing unit: "*First we need to gather all the data. And when we have the data, we can try one AI model".* B4 relied on a formal contract that specified in advance how many hours it would take to ensure efficient data management and what should be achieved within these hours: *"We ended up with a fixed price per hour. (...) They estimated 100 or 150 hours to do the first calculations"*. However, B4 encountered difficulty when collecting the data:

"We learned very quickly that the sensors we had in the machine were not giving the correct data. They were not accurate enough. Okay. So we spent some months changing sensors and trying out the different positions of the sensors and changing the way we were controlling the process."

As wrong data was collected, B4 emphasized that flexibility in the contract was required: *"In the end we were missing 20-30 hours. It was a difference, as we couldn't see anything. But then we added 20 hours and then we could finalize everything."* Flexibility was needed as they realized that the sensors were not collecting the right data. More hours were needed to deliver

a complete solution and adjustments were made towards the end of the relationship to enable proper data collection. Accordingly, B4 faced uncertainty as they did have capabilities to collect the right data, which could be mitigated by receiving help from S1 through data acquisition (Aben et al., 2021). Further, the contract showed completeness as price and delivery were established up-front (Artz and Norman, 2002). Indeed, B4 faced transaction costs from preparing the contract in order to specify price and delivery. As B4 did not have the right data when starting the relationship with S1, the contract could safeguard B4 against unforeseen contingencies (Williamson, 1996). However, as the problem with wrong data collection arised, relational governance played an important role to complement the contract as flexibility in the contract was required (Poppo and Zenger, 2002). Accordingly, the contract left room for adaptation to fully complete data collection by making adjustments in the contract, i.e. adding 20-30 hours after signing the contract. Further, relational governance was not only characterized by flexibility but also information exchange, as B4 shared important information about their business operations (Um and Oh, 2020). To conclude, B4 let contractual and relational governance act as frames to mitigate uncertainty in their relationship with S1 (Aben et al., 2021). Contractual and relational governance were used as complements (Poppo and Zenger, 2002) to ensure efficient data acquisition in the relationship before data transformation could take place.

Last, except for B4 all the buyers interviewed had the infrastructure in place to collect the right data. However, B3 had the infrastructure but also needed help to collect the data: *"They (S2) gather the data"*. B3 had developed an investment app to their end users that enables end-users to listen to quarterly calls while having access to the transcript at the same time. Accordingly, B3 needed help from S2 to acquire the data, i.e. the audio, before data transformation was possible through data labeling so that the text and audio would be synced.

In brief, the buyers interviewed had the data in place but needed help from their suppliers to transform the data into insights to solve their business problem or automate processes. Indeed, their data capability uncertainty was not mitigated through data acquisition but data transformation, which will be presented and analyzed in the following section.

4.3.2 Data transformation

In their relationships with their suppliers most buyers interviewed had the right data and the right infrastructure but needed help presenting the data in a logical way to provide valuable insights for their business or to automate a process based on their data. Accordingly, the buyers did not have capabilities to transform their data into business insights or automate business processes. The suppliers could help the buyers with this uncertainty through data transformation (Aben et al., 2021). This type of uncertainty could be mitigated by the suppliers helping the buyers as they put the data into an algorithm so that it would provide insights for their business problem or by machine learning.

First, one empirical finding was that the buyers did not have data capabilities to improve offerings towards their end-users. Accordingly, the buyers interviewed needed help with data

transformation. This was the case in the relationship between B3 and S2: *"They (S2) label it and then they train the model."* At first, B3 explained their relationship with S2 as purely transactional. There was a clear task B3 needed help with and when they contacted S2 they knew that S2 would be able to help them: *"It's most often important to know if the counterparty can solve the problem or not. Then you look at the terms of the deal and so on."* Apart from the contractual terms, B3 emphasized the relational aspect as well. B3 was happy that S2 could provide flexibility:

"So there are other players that can do that (time stamping), but then it's about flexibility and especially the time from that you send in a big mass of the text and then get it back with timestamps. That's also something that we took into account."

Flexibility was important for B3 when working with S2 as that enabled efficient data transformation:

"We have transcripts of all the publicly listed companies. And when the transcripts come, we need them to be time stamped quickly because they need to get into the app so people can follow along with the transcripts while they listen."

Both the contractual terms and flexibility was emphasized as important by B3 in their relationship with S2. In the end, B3 chose to continue the relationship with S2 by doing an additional project with them: *"So with X (S2), we're trying to train a model for another thing that we want to do. If it works, we'll purchase that from them as well."* For this solution, the contract was not complete from the beginning. To conclude, B3 faced uncertainty that required S2 to help them with data transformation to ensure efficient data management (Aben et al., 2021), as the data they had was not usable without the time stamping and machine learning. Governance acted as frames to enable efficient data transformation together with S2 (Aben et al., 2021). B3 faced high transaction costs as they wanted their contract to be predictable and used contractual governance to enable completeness in their contract when it came to price and delivery (Artz and Norman, 2002). Due to high transaction costs, B3 emphasized that uncertainty was also managed through developing the relationship with S2 (Dyer and Singh, 1998, p. 662). B3 emphasized that they wanted flexibility when working with S2 so that the data transformation could happen quickly and on demand. Also, B3 said that they wanted to extend the relationship by doing an additional project with them. B3 used contractual and relational governance as complements as both were used in the relationship with S2 (Poppo and Zenger, 2002).

Next, in the relationship between B5 and S3, B5 already had their data in place but uncertainty as they did not have capabilities to improve data that could be used to improve their customer offering. Thus, B5 needed help with data transformation (Aben et al., 2021): "*S3 in this case they are helping us to, yeah, to explore the data, we already decided to collect."* B5 emphasized that splitting up the payments into smaller parts was important in the beginning as they could not visualize what S3 would deliver to them: *"In the beginning we ordered shorter, more*

specific tasks for 1-3 months and towards the end we have done it more on an ongoing basis with 30 day's notice." Further, B5 emphasized mutual information exchange by B5 sharing information about their business operations and S3 sharing their knowledge and capabilities:

"*We have the domain knowledge. And even if they are good at machine learning/AI, in the end it's good to have some understanding from the physical world around our application. So I think we have a very good partnership and the team is working to support each other from our different knowledge and experience."*

In brief, B5 managed uncertainty by splitting up payments through short-term and detailed contracts when it came to price and delivery (Artz and Norman, 2002). There were high transaction costs incurred as there was a need for fully predetermined contracts (Williamson, 1996). This was mainly emphasized in the beginning of the relationship as the formal contract could safeguard towards uncertainty during the initial stages in the relationship (Larson, 1992). As the relationship progressed, the completeness of the contract in terms of delivery as well as predetermined contract duration did not have to be specified in advance to the same extent and instead turned into an ongoing agreement between B5 and S3. Further, B5 exemplified relational governance as they thought it was important with mutual information exchange, which was done by B5 sharing information about their business operations and S3 information about data transformation (Poppo and Zenger, 2002). In brief, B5 used both contractual and relational governance to complement each other to manage uncertainty in their relationship with S3.

Moving on, B1 explained that they faced uncertainty regarding the data that could be used to improve their customer offering, and thus wanted help with data transformation. B1 explained that they managed uncertainty by splitting the payments using a formal contract: "*We paid a third up front and then a third like two months later and the last third one when it was delivered."* B1 argued that as they were "*tech-savvy enough*" to understand their business problem they wanted to specify price and delivery of the task already from the beginning. Further, B1 explained that an important part of the relationship was acting solidarily on price:

"*Why not just speak frankly and openly like "this is what we need, work with me." Give me a price that works for both of us and then we can move onwards because it's a much more natural way of discussing."*

B1 explained further that, as they were not prepared to pay too much to S1, they compared the price of the big data solution with doing it in-house:

"Because we already had an idea of how problematic this was, we knew that if I put one of my guys on it, he would fix it. Maybe it would take him a year to do it and that would maybe cost me a million Swedish kronor because of salary and everything, right? But if you're contacting someone that's best at it, it's not going to take them a year to do it right."

B1 was subject to uncertainty and managed this through data transformation together with S1 (Aben et al., 2021). Contractual governance was used through explicit contract terms when it came to price and delivery in order to control efficient data management (Artz and Norman, 2002). However, as B1 considered the transaction costs to be high, they considered vertical integration by doing the task themselves in-house (Poppo and Zenger, 2002). Further, solidarity when it came to pricing was emphasized by B3, and accordingly relational governance was used to complement the contract. Relational governance reduced transaction costs as B1 and S1 could decide on a price that both agreed on. Relational governance acted as a complement to the contractual arrangement to split payments into smaller parts.

Next, B2 also faced uncertainty and needed help from S1 to successfully transform their data so that they could use it for price prediction purposes. Nevertheless, B2 had a large database, but needed help to make sense of the data: "*We wanted to find an agency that can explore together with us how to build value in using AI across a large data set and very complex, you know, pricing factors across hundreds of thousands of data points."* B2 explained that the project was a gamble to them: *"You know, you don't really know what you're gonna get."* Further, B2 explained that they managed this by splitting the payments into smaller parts as well as by making adjustments along the way:

"Let's take it to the first step and then we have a joint review of where we are and what we think can happen and what we think is good and what we think didn't work and then we take the next step. So in that way you don't expose yourself to the full investment up front, but you will expose yourself only to parts of it."

B2 emphasized mutual information exchange as they worked together with S1 to enable data transformation: *"You're learning and both parties are gaining a lot of insight and understanding about each other and the problem statement."* Also, there was flexibility as changes were made along the way:

"Halfway through you might change certain things because you see that the aspirations we had initially are probably too far fetched and it's not gonna work and we're not gonna get that accuracy we need."

B2 managed uncertainty by safeguarding themselves through contractual governance. B2 experienced the transaction costs of the project to be high (Williamson, 1996) and managed this by not paying the full investment up-front. Also, B2 emphasized that it was necessary to make adjustments in the contract, as there were unforeseen contingencies with the data (Poppo and Zenger, 2002). As there was high uncertainty, relational governance was invested in as well (Paolucci, 2021) and data transformation could not be efficiently carried out without flexibility in the contract. Accordingly, B2 used contractual and relational governance as complements to manage uncertainty regarding data transformation.

Moving on to B7 and S4, B7 explained that they wanted help transforming their data as they wanted to automate processes using data they already had in their organization: *"So I started to realize three years ago that automating processes and having the help of robots was actually something that we needed to look more into."* Also, B7 explained that one process they received help from S4 transforming was automation of supplier invoices:

"We have a robot that is currently reviewing all of our incoming invoices, so all supplier invoices. In the final step of all invoices before actually going into payment, the robot is doing a certain number of controls for us to make sure that the amount is not like over a certain amount that we've decided on."

Initially, B7 explained that after having done workshops with S4, a complete contract could be set based on price and delivery:

"What we're doing is that we're having a workshop where we go through the process that we want to automate, we send this to S4 and they do their analysis, how many hours will this take in order for them to develop? And then they come back to us with a suggestion that, alright, this will take us 40 hours and the cost of this will then be X."

B7 highlighted that the price of the service offered by S4 was compared to the costs of continuing with "business as usual":

"And then it's up to us to either accept or if we feel that no, maybe the price is too high compared to the actual number of hours we were putting into this process. So let's continue to do it manually."

After successful data transformation, the contract form was then adjusted to a monthly subscription fee as all processes were successfully automated: *"So they have like a fixed number of X euros every month, and then you get everything included in this price."* B7 explained their relationship with S4 as contractual, and that the relationship was a bridge towards successful procurement and implementation of the big data solutions. B7 emphasized that in their relationship with S4, there were explicit contracts ordered with short and predetermined duration that evolved into a contract on an ongoing basis. On the other hand, B7 also highlighted that trust was important when working with S4. When explaining what they thought was most important when working with S4, B7 said the following:

"Being able to help us out with the processes afterwards in order to automate but also that they're very friendly. It was very personal, and the chemistry was there from the beginning. So I felt safe with them and it was also people that I wanted to work with. So that was like the main reason I would say."

To clarify, B7 faced uncertainty that was mitigated through data transformation by the help of S4 (Aben et al., 2021). As the uncertainty entailed high transaction costs, they considered

engaging in a short-term exchange with S4 by letting them analyze which processes were feasible to automate and then decide to do them manually if the price would be too high (Poppo and Zenger, 2002). By resorting to contractual governance, with a detailed contract that specified in advance how many hours the project would take B7 could safeguard against uncertainty. Completeness of the contract and predetermined contract duration was more important in the beginning of the relationship to safeguard against uncertainty during the procurement (Larson, 1992), and the contract later evolved to a monthly fee. However, trust was also an important feature for B7. B7 emphasized trust as a characteristic to determine the credibility of S4. Accordingly, contractual and relational governance were used as complements by B7 (Poppo and Zenger, 2002) to enable efficient data transformation.

In the above mentioned relationships the buyers brought up both contractual and relational governance to manage uncertainty with data transformation. However, in the last relationship the buyer only emphasized contractual governance. B6 faced uncertainty as they did not have data capabilities to transform their data and they needed external expertise from S5 to mitigate this uncertainty: *"We had a lot of data, we had the infrastructure, but we didn't have it in one place. So that is, that's the way we decided to solve it."* B6 needed help to ensure efficient data transformation: "*In the end, you still need to understand your data."*

They showed their view of the relationship was more of a transaction rather than a relationship. They wanted to pay by splitting the project up into smaller contracts first and then extending later on as the relationship evolved:

"We paid per hour and per person that helped us. Pre-work and offer were for free. Approx X SEK/hour. We started with a 2x3 months contract and then we increased to 3 people over 6 months."

After having ordered short contracts with predetermined duration they changed to an ongoing contract with mutual notice period: "*We have an ongoing contract with mutual notice period today."*

B6 faced uncertainty that was mitigated through data transformation by the help of S5 (Aben et al., 2021). Predetermined duration and complete contracts were ordered (Artz and Norman, 2002) that later evolved to ongoing basis. Accordingly, completeness of the contract and predetermined contract duration was more important in the beginning of the relationship to safeguard against uncertainty during the procurement (Larson, 1992). The focus on contractual governance and lack of emphasis on relational governance implies a substitutive relationship to governance (Lumineau, 2017).

In brief, in the above mentioned relationships, contractual and relational governance were used as complements except for in the case of B6. Some of the buyers, B5, B6 and B7, valued contractual governance in the beginning of the relationships and thought completeness in the contract was less critical as the relationship evolved.

Second, another empirical finding was that suppliers, S1, S2, S4 and S5, used contractual governance to mitigate uncertainty among buyers in general. S1 explained that such buyers approached them with large volumes of data but needed help transforming the data. Such data transformation constituted using the buyers' historical data to train an algorithm in the development phase and applying real time data from the buyers' daily operations in the implementation phase. To manage uncertainty S1 explained that they split up the problem into smaller parts. By doing several projects with the buyer and starting with the easiest one, S1 managed uncertainty with the respective buyers:

"We always try to find a small project, some kind of a proof of concept, something. So that's always, it's a simple problem for them to solve. This is what they have as internal historical data and we can use a mature solution. So that first project will not be too complex for them and our first project with them will not be so complex."

S1 managed uncertainty by matching one of their solutions with the data that the buyer already has:

"So we identify problem areas they have and sort of identify what kind of data they have already and then we say OK, you have this problem and you already have historical data connected to these problems and here is an AI technology that's a perfect fit for this problem with this data."

The data could then be transformed into valuable insights. By doing this, S1 managed to split the problem into smaller parts and choose to focus on one part of the AI journey as a start. The contracts would then be complete to a higher extent as the scope would be more well-defined and narrower. However, S1 explained that there were cases were the scope might change towards the end of the project, as the buyer chooses to extend the use of the AI application:

"From the beginning we were supposed to just run the service in one factory in Sweden, but in the end they want to run this solution in five countries on 20 locations. That sort of stuff changes the scope."

Moving on, S4 said that they provided their buyers with a roadmap of their AI journey. This strategy enabled S4 to split the problem into smaller problems by starting with an easy project and do more complex projects later on in the relationship: "*The whole project is just a chopped-up roadmap with technical deliveries and the technical requirements."* Further, S4 explained that the start of the road map is "*the low hanging fruit"* to show the buyers that data transformation is feasible. Moreover, S4 explained that this enabled completeness in the contracts so that the buyers understood what would be delivered: *"And all the requirements we make sure that the customer knows, what the requirements are, and what we do, and then we're more likely to have a happy client."* Also, S4 emphasized the importance of staying within the scope when working together with the buyer to enable such complete contracts:

"Through the project we do only what's in the scope. We never add stuff in the scope. We just go for the scope and we keep the scopes regardless if it's more than from the beginning. So we never develop like the biggest project, you start with a very small scope."

S4 argued that staying within the scope was reinforced by providing an algorithm with enough accuracy to create value for both parties, and improving it later along the way:

"We believe that we can make it (the algorithm) 90% accurate. We know that if we can make 50% that we have a business value, because if we get the results then we earn this. So the longer aim is to come up to 90%, but so far we've built the baseline model for the lowest bar that it would still have business value."

Next, S5 also emphasized starting with easy projects by looking at the profitability of the projects: *"What margins do we have on our different projects? They don't even know and so we'll help them with the easy stuff first and then go to the more advanced stuff."* S5 explained further that this strategy enabled them to maintain relationships with their buyers as they would continue working with them on their AI journey. Accordingly, S5 managed uncertainty among buyers by splitting the large "AI project" into smaller projects:

"But in the basic stuff there's a lot of value as well. So when they start realizing the value that we can contribute to them, they will want to do more stuff with us so we usually come to our customers to get inside the doors, take them by the hand and take them on a journey."

Further, S5 explained that this strategy enabled them to develop long-term relationships as the customer would order short complete projects to continue their big data journey. This was especially the case when buyers were less mature with their data:

"I'm proud to say that most of our customers have been with us for a long time. So we have long relationships and I think that is also important in what we do, for example, if they are less mature."

Last, S2 emphasized completeness of the contract by specifying price and delivery in advance: "*Before we start this is quite large like integration or proof of concept. We have to set some terms like "how much are you gonna pay for us doing the proof of concept?""* Further, S2 highlighted the importance of contract completeness regarding data management: *"When you sign up for our service, there's a "terms and conditions" that says things on how we are a sub-processor of their data and all that stuff and then of course, we try to do as much as possible in terms of security."*

Accordingly, S1, S2, S4 and S5 managed uncertainty by offering easy projects within a small scope and staying within this scope throughout the project. By splitting up the business problems into smaller parts the suppliers used contractual governance (Gelderman et al., 2015).

The contracts specified in advance what the supplier would deliver to the buyer and the degree of completeness was therefore high in terms of delivery and the projects offered were for a shorter duration (Arts and Norman, 2002). Rather than risking unforeseen contingencies suppliers safeguarded themselves by providing short-term projects where such risks were lower. The suppliers calculated the business value of their projects and did not exceed beyond the scope of that business value as it was defined in the contract. However, S1 allowed for some flexibility in the contract to make adjustments later on after contract signing as the buyer would want to scale the project. Nevertheless, the suppliers managed uncertainty by engaging in data transformation mainly through contractual governance (Aben et al., 2021). Also, suppliers still managed to sustain long-term relationships with their buyers using such contractual controls. Accordingly, the suppliers tended to use contractual governance as a substitute.

To conclude, the buyers were faced with two types of data uncertainty when working with their respective suppliers, i.e. data acquisition (data collection and infrastructure) and data transformation (Aben et al., 2021). The buyers explained that they managed these uncertainties using two strategies in their relationships with their suppliers. The strategies used were (1) splitting payments into smaller parts (2) being transparent and communicative. These strategies were mainly used as complements throughout the relationship with their suppliers. The suppliers engaged in contractual governance to mitigate the data uncertainty by splitting up the problem into smaller parts, staying within the scope of the project and starting with the simplest project.

4.4 Digital ecosystem uncertainty

Except for the technical challenges when it came to specification of business problems and data management, there was a gap regarding the digital ecosystem of buyers. Suppliers talked about this gap among buyers in general. It was identified that buyers started applying the big data solution that they had developed together with their suppliers and required a continuous transformation process and a long-term partnership. This gap is based on the fact that (1) employees in the company lacked digital skills and thus had trouble adapting to the big data ecosystem (2) the operating process and organizational structure did not fit with the new data-powered system.

The suppliers argued that buyers do not have the capability to successfully use the big data solution application due to a weak fit with the digital ecosystem in multiple dimensions. S1 summarized and emphasized this: *"They're not either mentally prepared or they are not there. They don't have the right organization."* Three dimensions of digital fit were identified that were recurrent with regards to big data solution applications in medium-term and long-term visions: employees, organizations (operations processes and company structure), culture.

4.4.1. Employees: lacking digital education

S5 highlighted that employees (both digital talents and non-digital talents) constitute a crucial component in the organizations and are the key to the success of the digital transformation preventing buyers from engaging in successful procurement of big data solutions:

"One of the hardest things for those companies is, yeah, sure we can find out a lot of things. We can do a lot of cool stuff with data but you as a company have to transform as well. So there's a transformation that needs to be done within the company for the people working in the company. To actually start using the new technology because if they don't then there will be no change."

S5 exemplified this problem further by talking about data acquisition and data transformation:

"Say we were to help a customer gather data and we have a lot of sales data and we want to use it for pricing. So we do that, and we set up a pricing model that uses a lot of data to analyze. Then, say for this product or this combination of products you should set this price. But if the company or the salespersons don't use that information, then there's been no change and that is, of course, obvious but it's really hard to get someone to change the way that they are working."

Moving on, among all the diverse departments within an organization, the IT department accounts for a pivotal part of digital transformation with all the digital resources and digital talents. One inevitable reason for the failure of big data projects is resistance in the IT-department. S3 exemplified this uncertainty by talking about old IT-systems:

"*The mindset of the IT people in a company, they don't wanna change. They are so careful about their systems and I understand why. Imagine if you rebuild a 90s system in a company, all the business will die."*

S1 also emphasized the IT department as an important gatekeeper when meeting with the buyers: *"Understand the IT department, sort of understand, is there a white male person of 50 years that will be a problem for you?"*

The suppliers managed this uncertainty through education. S1, S3, S4 and S5 talked about educating their buyers. S1 explained that they do workshops with their buyers where they show a subway map as a visual aid that describes what they can offer (i.e. machine learning, optimization, decision trees, genetic algorithms etc). In these workshops, buyers explain the business problem while S1 explains how big data solutions could help them. During the workshops S1 asks buyers questions regarding their business: "*Are the competitors doing anything better? Trends in the industry? Does the CEO, do they have any problems that affect them so they can't sleep during the weekend?"* S1 explained further that they discuss accessible data together with the buyer: "*We have a dialogue about the data, how much data you have, the quality of the data. And do you have a different system? Is it difficult to download the data?"*

Next, S3 explained that it is crucial to educate buyers as that will help them on their big data solution journey: *"They need a lot of support on all these issues on how to implement and how to modify the business and how to make data accessible and what is the next decision in this project."* S3 said that they offer introductory courses to buyers to educate them on which solutions are feasible for them to help buyers with:

"*So we invite people to learn more about AI by participating in various educations that we have and that are mainly aimed for management in companies like CEO's and the steering boards and so on."*

S3 explained further that their aim is to introduce potential buyers to big data solutions so that they have more knowledge on what big data solutions can do to solve their business problems: *"We can't change such a company because that's too big a bite. But we can start the process. We can point that at the need, we can help them with education, but the process."*

Moving on, S4 explained that their mission is to help companies on their big data solutions journey: *"So the thing is that the mission I have is to enable more AI and to implement applied AI into our society.* Further, S4 does case studies with their buyers as a way of educating them:

"When we talk to CEOs or they don't know "so what can you do?". So then the first thing is to let them know, like what is AI? What is your condition? What can you do and then have like case studies so they can grasp."

Last, B7 confirmed that suppliers intend to help buyers to construct an agile and ideal organization and operation process:

"*It was basically just S4 that I felt actually offered the whole package like with the training and also being able to help us out with the processes afterwards. (...) They have also been of help and like having workshops I've done that now, to a certain degree on my own, but also having their help and workshops with them with analyzing different processes, on different departments and coming to a conclusion on whether it's worth to automate with the help of a robot or not."*

4.4.2. Organizations: unmatched digital process

S1 further highlighted that the big data solution that a buyer may want to apply does not match current business operations:

"It's very, very common that people do the most complex projects that they need to change their business idea. And this is one of the reasons why 92% of the AI projects fail. They do it way too complex."

S3 highlighted that, as buyers aim to do too difficult projects the uncertainty is apparent as the company's inherent structure and business processes does not fit with the big data application: *"Not because of the technical issues, but because the organization and the process still didn't fit."* S3 further argued that there is a need for a cultural change for companies to be able to do more advanced projects. S3 explained that they encountered big data solutions projects that failed: "*fail in the sense that they never become something that the customer or the company uses."* S3 further argued that the reason for this is the internal challenges:

"It's very easy to do an AI product or an AI project up to proof of concept. Like let's extract some test data. Let's build something in my laptop and, hey look, we can detect all customers that are about to leave our service. Cool, let's implement it. And then you meet all these impossible challenges internally."

To sum, in the buyer-supplier relationships there was motivation bias, data capabilities uncertainty and digital ecosystem uncertainty. The motivation bias could be managed through nudging, data capabilities uncertainty through governance and digital ecosystem uncertainty through education. Nevertheless, in line with our research question and identified research gap, governance and nudging strategies will be discussed in relation to previous research to motivate our theoretical contribution derived from the empirical analysis.

5. Discussion

In this section, the empirical findings will be discussed and connected to previous research. Theoretical contribution to inter-organizational governance and nudging will be motivated.

5.1 Theoretical contributions

5.1.1 Contribution to inter-organizational governance

This study contributes theoretically and empirically to the literature on governance of private-private relationships. This is done by exploring the interplay of contractual and relational governance in the context of data acquisition and data transformation. Further, this study contributes to the governance literature by studying both supplier and buyer perspectives in one model.

First, our findings imply that contractual and relational governance are used as substitutes by suppliers and as complements by buyers to enable efficient data management. This is in line with previous findings in other contexts (Um and Oh, 2020). Our empirics show that suppliers use contractual governance to safeguard themselves against taking on projects with lower success rates and instead offer simple and mature solutions. The suppliers value offering buyers short and complete contracts and staying within the scope of the contracts with the aim to deliver least possible effort required to the buyers while still creating business value. This is similar to findings in other studies that argue that suppliers are less inclined to provide innovation-oriented activities to their buyers (Um and Oh, 2020). Our findings imply that

suppliers are less inclined to provide innovative big data solutions but rather want to offer solutions that are mature and guarantee success. However, we have identified in our findings that there are tendencies towards relational governance among the suppliers as well. Our findings indicate that there are cases where there is adaptation in the contracts. This may be the case because suppliers' resort to a compartmentalization strategy, using contractual and relational governance separately from case to case (Lumineau, 2017). Moreover, findings in other studies argue that suppliers value relational characteristics such as transparency in order to build trusting relationships (Paolucci et al., 2021, Aben et al, 2021). In our empirics, it was only the buyers that emphasized relational governance, such as mutual information exchange, by explaining that they shared knowledge about their business operations and the suppliers' knowledge about big data solutions. The suppliers rather saw it as a one-way exchange by educating the buyers on big data solutions. Moving on, our findings imply that buyers use relational and contractual governance as complements throughout the relationship. Our findings show that buyers use relational governance throughout the relationship to manage uncertainty of data capabilities, while contractual governance is mostly valued in the beginning of the relationships. Accordingly, completeness in the contract and predetermined contract duration was less important later on. Apart from seeing the relationship as a mutual learning process, characteristics such as flexibility and solidarity were emphasized as well. This is in line with previous findings that say that relational governance plays an important role for buyers when purchasing services (Gelderman et al., 2015). Also, it implies that the buyers perceived that they faced less uncertainty as the relationship evolved, and that most uncertainty was faced at the procurement stage and less at the implementation phase. This is in line with previous findings that say that buyers think that contractual controls are more important at the first stages when purchasing a service and that relational governance is adequate with regards to implementation issues (Gelderman et al., 2015).

Second, in the context of data management, it was implied by our empirics that contractual governance guided data transformation activities. It was identified in our empirics as suppliers mainly used contractual governance in their relationships with buyers. This is in line with previous research that argues that contractual governance is more critical for suppliers to ensure efficient transactions with their buyers (Um and Oh, 2020). In the buyer-supplier relationships explored, the buyers enter the relationships after having managed successful data acquisition on their own. In the relationships, buyers managed uncertainty with data transformation by splitting payments up so that they would not face the full investment up-front and by being transparent and communicative. They emphasized the relationship as a mutual learning process. Accordingly, suppliers emphasized contractual governance while buyers emphasized both contractual and relational governance to manage efficient data transformation. Aben et al. (2021) has studied data acquisition and data transformation in public-private relationships and their findings imply that contractual governance is less prominent in data transformation activities. They further argue that this is the case due to difficulty in defining detailed specifications for data transformation. In our empirics, suppliers manage such challenges by splitting up the business problem into smaller parts and starting with the easiest project resulting in less complex and more mature big data solutions. Aben et al. (2021) argue further

that it is rather data acquisition that entails uncertainty for buyers when engaging with their suppliers. This is the case because in public-private relationships, lack of motivation for suppliers to acquire desired data requires contractual governance including incentives and punishments. In their study, value-maximization and social interest conflict with one another. In our study, as private actors inherently have alignment on economic value creation, this is not an issue. Rather, our findings show that suppliers are inclined not to engage in data acquisition at all with their buyers but rather focus on projects that include only data transformation.

In short, to manage efficient data acquisition and data transformation in private-private relationships, buyers' resort to a complementary relationship between contractual and relational governance, while suppliers use a substitutive one. Accordingly, buyers and suppliers perceive their use of governance mechanisms differently (Um and Oh, 2020). Our empirics have most implications for data transformation, as the buyers interviewed faced ambiguity with the data already acquired.

5.1.2 Contribution to nudging theory

Our study contributes to explaining how suppliers may manage high expectations from buyers with regards to the specification of the big data solution by using nudging. This is done by studying the supplier perspective more thoroughly to distinguish which strategies they use to manage buyers who are subject to cognitive biases in their specification of the big data solution.

Our empirics show that buyers are subject to cognitive biases as they have high expectations on which big data solutions the suppliers could offer. This problematizes how the specification that the buyer has to the supplier may prevent an efficient relationship. Our study contributes to a new context where cognitive biases and nudging may be found. In line with the findings of Gelderman et al. (2015), service specifications change throughout the buyer-supplier relationships. However, while Gelderman et al. (2015) captured the buyer perspective and their use of relational governance to manage this in the relationship, our study contributes by looking at the supplier perspective. This was carried out by exploring how they manage incomplete information in the specification of the big data solution in the relationship. Further, van der Valk and Rozemeijer (2009) argue in their study that, as buyers do not have enough information to specify their needs in advance, more information from the supplier is needed before engaging in the relationship. By looking at specifications in the context of big data solutions, our study highlights that suppliers manage incomplete information by nudging their buyers to accept solutions that the suppliers want to offer them. Nevertheless, in theory incomplete information results in adequate rather than optimal solutions (Simons, 1955). Accordingly, it is implied that rational decision making could be committing to a project that would fail or deciding not to purchase the solution from the supplier. The natural question to ask is then what would happen if the buyers were not nudged? Moving on, in line with Thaler and Sunstein (2009), a nudge should significantly alter decision making, which is identified in our empirics as the buyers purchase solutions that are successful and less complex compared to the solutions they expected from the suppliers. Moving on, our empirics show that nudging is done by information

placement and warning messages to manage cognitive biases among buyers. The suppliers aimed to provide information of incompatibility in the beginning of the relationship. The findings of Esposito et al. (2017), imply that information should be provided at the payment stage. However, as buyers in our study split their payments it is not necessarily contradicting those findings. Last, in the context of data management, our empirics show that nudging results in suppliers helping buyers with data transformation rather than both data acquisition and data transformation. As the suppliers aim to offer less complex projects with short predetermined contracts the result is buyer-supplier relationships where the suppliers move directly to the data transformation part and skip the data acquisition step.

6. Conclusion

This thesis has had the purpose to explore governance and nudging in buyer-supplier relationships of big data solutions. Using inter-organizational governance and nudging theory, the aim was to answer this research question:

How do big data solution suppliers and buyers manage efficient relationships using governance mechanisms and nudging?

We contribute to literature on inter-organizational governance and nudging by exploring how buyers and suppliers manage data capability uncertainty and cognitive biases in the relationship. First, we have seen that suppliers use governance as substitutes to manage buyer uncertainty, and that they resort to contractual governance to safeguard themselves in the relationship. They aim for contracts that are within a narrow-predetermined scope to minimize the effort required while still creating business value. They also start with simple and mature solutions and extend their relationships as buyers purchase more solutions later on. We saw some degree of adjustment in the contracts, highlighting that the suppliers may use relational governance from case to case. Nevertheless, suppliers experience their relationships as one-way information exchange as they educate buyers on big data solutions. Second, we have seen that buyers use governance as complements to manage data capability uncertainty. More specifically, they aim to use contractual governance to not expose themselves to the investment up-front by splitting the payments up and relational governance as they see the relationship as a mutual learning process where trust, flexibility, and openness play an important role. The buyers are also willing to allow for less complete contracts with unspecified duration as the relationships evolve. Last, we have seen that suppliers use nudging to manage incomplete information among buyers that want to procure big data solutions but have too high expectations. Buyers have too high expectations about which big data solutions could be provided from the suppliers. The nudging results in buyers purchasing solutions that include data transformation rather than both data acquisition and transformation. The suppliers may then engage in solutions for which the buyers have successfully managed data collection on their own before entering the relationship and where data transformation is required to manage data capability uncertainty.

6.1 Practical implications

Our study highlights the importance of managing the buyer-supplier relationship in big data solution projects and has implications for practice. To start with, our study identified three obstacles when procuring big data solutions: motivation bias, data capability uncertainty and ecosystem uncertainty. These three main barriers could help increase the mutual understanding between the suppliers and buyers: suppliers may have a more proactive plan to help buyers better understand their business problem and their current capabilities of data acquisition and data transformation activities. Correspondingly, buyers may create a better vision about what is problematic with the current internal operations and business models, what big data solutions could help to improve or transform them, and where should they put efforts within big data tools. Further, our study has provided insights on which strategies may help improve procurement of big data solutions. Suppliers of big data solutions help mitigate uncertainty with regards to data acquisition and data transformation with potential buyers and current customers by using contractual governance and nudging. In addition, this study recommends that education on big data solutions should accompany the digital transformation progress.

6.2 Limitations and further research

First, a limitation is that the buyers we interviewed had structured data acquisition in place so that the suppliers could help them exclusively with data transformation. Further research could be to study more cases where data acquisition was managed with the suppliers where nudging was not efficient. Secondly, generalizability to other services is a limitation as the relationships of other services may not include cognitive biases and data capability uncertainty of big data. However, as more and more companies are going through digital transformation, the need for big data solutions may be applied to more industries. Further research could study how big data solutions could more efficiently be applied to different industries, perhaps by focusing more specifically on automation and machine learning. Last, as our conceptual model did not incorporate digital ecosystem uncertainty and education, further studies could study more closely how big data solutions could be incorporated in organizations through education.

7. References

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8. Appendix

Appendix A. List of Interviewees

Interviewee	***Role***	***Length***	***Date***
Buyer 1	CEO/founder	49 min	30/8
Supplier 1	CEO/founder	54 min	1/9
Buyer 2	CEO/founder	32 min	9/9
Buyer 3	CEO	26 min	13/9
Supplier 2	CTO/co-founder	47 min	14/9
Buyer 4	COO	29 min	15/9
Supplier 3	CEO/founder	53 min	5/10
Buyer 5	Head of R&D	59 min	7/10
Supplier 4	CEO/founder	41 min	14/10
Supplier 5	CEO/founder	36 min	17/10
Buyer 7	Head of Finance Operations	31 min	7/11

Appendix B. Interview Guide

General Question: How do AI buyers manage supplier relationships and implementation?

Research Questions:

How do AI buyers manage supplier relationships using governance mechanisms?

- What does AI service procurement look like?
- How to manage the information gap among buyers?

Initial general questions/Warm up questions

From our side

1. Brief self-introduction
2. Brief intro of our purpose
    - Buyer- supplier relationship, look at procurement and implementation of AI services in a B2B-context
    - research study (interview-based, to contribute valuable ideas for AI suppliers)
3. Ethical considerations:
    - participation is voluntary
    - what is said during this interview will only be used for our thesis
4. Can we record the interview? For transcription purposes.
5. Name and company will be anonymous!

6. If we want to use quotes we will ask you to confirm.

From interviewee side

1. Educational and professional background and experience?
    - years in industry and current position?
2. Market position? Competitors? Competitive advantage?

Part 1: AI procurement, as a background info checking

For buyer

1. Importance of this AI procurement, main benefits from the project
2. Problem identification, why did you want to procure AI in the first place?
3. Supplier selection
4. Procurement process
    - Initial contact & meeting
    - More specific problem definition
    - Data extraction
    - Initial testing
    - Prototype/Proof of concept
    - Contracting and pricing: How did you manage the contract? E.g. payment, add-ons after signing?
        - Anything unclear with the contract? How was this managed?
5. Implementation, AI application
    - New issues coming up?

For Seller

1. What sorts of clients do you have?
2. IT department?
3. Why start an AI business?
4. What's their core AI capability?
5. Any marketing strategy? Any further plan to increase the sales or reputation?
6. The AI knowledge of various customers in general
7. The main obstacles (for the buyer) you can identify in the AI service you provide?
8. Any failure cases you can share with us?

Part 2: Information uncertainty, as the main problem identification

For buyer

1. Start from the data management: easy to provide the database for the supplier or not?
    - How do you manage this?
2. Did you feel confused when the supplier talked technical words during the communication?
    - How did you manage this?
3. Was there any issue that seemed especially complex?
    - complexity: you are not sure what the end-product will be like

- How did you manage this?

For seller

1. Could you quickly go through the process, from problem definition to implementation phase?
    a. If not mentioned already, who does the initial contact?
2. Start from the data management: easy to get the database from the customers or not?
    - How do you manage this?
3. Difficulties in the communications: for example, the customer can't understand the technical words you talk about
    - How do you manage this
4. Was there any issue that seemed especially complex?
    - complexity: the buyer is not sure what the end product will be like
    - How did you manage this?

Part 3: Value co-creation & Mutual learning, as a result-oriented analysis

For buyer

1. Based on the results/outcome, do you think it's a valid project?
2. Could you specify the outcome with more data, for example working efficiency, business sales, user quantity (…)?
3. Do you have further planned in AI procurement?
4. What did you learn from the relationship?

For seller

1. Based on the evaluation of the input and outputs, do you view the project you have done as profitable or not? (Sales performance)
2. Except for money, what are the main benefits you view from the projects & supplier-buyer relationships?
    a. What have you learned from the relationship?
    b. Example of a relationship you found especially insightful.
3. To sum up, what would you say is the biggest difference when procuring AI services compared to other services?
4. Would you like to share customer contacts with us?

Appendix C. Coding Table Examples

Citation	**First-order code**	**Second-order code**	**Theme**
"A challenge for them because often they have heard about something cool that you can	Business mindset gap	Motivation bias	Buyer has overly optimistic expectations

use AI for and they want to do that." *"Someone would say something like, can it configure my whole system?"*	Technology mindset gap		
"Like try to get them done quite early, like it (big data solutions) doesn't do this"	Supplier strategy	Strategy to manage bias	Set the bar low
"We wanted the time stamping part which is their AI, taking all the texts and matching it with audio."	Problem formulation gap	Information provided to supplier	Specification to supplier
"*First we need to gather all the data. And when we have the data, we can try one AI model"* "*S3 in this case they are helping us to, yeah, to explore the data, we already decided to collect."*	Implementation gap	Data collection uncertainty Data transformation uncertainty	Buyer does have capabilities to collect the right data Buyer does not have capabilities to transform data
"*We paid a third up front and then a third like two months later and the last third one when it was delivered."* "*Why not just speak frankly and openly like "this is what we need, work with me." Give me a price that works for both of us and then we can move onwards because it's a much more natural way of discussing."*	Buyer strategy	Strategy to manage uncertainty	Splitting up payments Being transparent and communicative
"*The whole project is just a chopped up roadmap with technical deliveries and the technical requirements."* *"So that first project will not be too complex for them and our first project with them will not be so complex."* *"Then we say OK, you have this problem and you already*	Supplier strategy	Strategy to manage uncertainty	Splitting business problem into smaller parts Starting with an easy project

have historical data connected to these problems and here is an AI technology that's a perfect fit for this problem with this data."			Provide a mature solution