THE DATA SCIENTIST

A CUCKOO IN THE MANAGEMENT ACCOUNTANT'S NEST?

CHRISTOPH BEIS

ANDREAS FRIEDRICH

Master Thesis

Stockholm School of Economics

2019

The Data Scientist: A Cuckoo in the Management Accountant's Nest?

Abstract:

Data Science has been one of the most used buzzwords on corporate agendas in recent years and with it, a new professional, the data scientist, has entered the organizational stage. Surprisingly, Management Accounting literature has not investigated the role of data scientists and their interactions with management accountants so far. Via a qualitative case study, we strive to establish a more nuanced and clearer understanding of the concrete tasks carried out by these organizational players and shed light on the interactions with management accountants. We find a strong overlap of tasks between data scientists and management accountants, including e.g. performance measurement and business partnering tasks. Despite a versatile interaction pattern between both focus professionals, data scientists proactively use the strong role ambiguity to expand their tasks as well as organizational status through role making and distance themselves from 'dirty work'. The main means applied in this context are the execution of expectation management, a monopoly on sophisticated Business Intelligence & Analytics systems and a strong top management support. Thus, we argue for an even stronger decoupling between management accountants and Management Accounting tasks than in the Enterprise Resource Planning (ERP) era. In contrast to authors, such as Quattrone (2016), we provide empirical evidence that management accountants are not able to retain their organizational position by taking on an interrogation role within the 'digital revolution'.

Keywords:

Business Intelligence & Analytics, Business Partner, Data Scientist, Information Systems, Interaction, Jurisdictional Competition, Management Accounting, Role

Authors:

Christoph Beis (41322)
Andreas Friedrich (41326)

Tutor:

Lukas Goretzki, Associate Professor, Department of Accounting

Master Thesis
Master Program in Accounting, Valuation & Financial Management
Stockholm School of Economics

Acknowledgements

We would like to thank the case company, InsurCo, for the support and access we received. Without their help we would not have been able to perform our analyses in this highly interesting setting. Our gratitude is especially directed towards all interviewees, who provided us with so many insights and much help throughout the whole process.

Besides, we would like to thank our tutor Lukas Goretzki, Assistant Professor at the Department of Accounting at the Stockholm School of Economic, for his support, comments and guidance. It was very inspiring and motivating to work on a topic that also you are so passionate about.

Finally, a big thank you is reserved for our families and friends, who have been a great source of support throughout our academic careers. Thank you for being there throughout all ups and downs.

Christoph Beis & Andreas Friedrich

Stockholm, May 2019

Table of Contents

1. INTRODUCTION 1
2. THEORETICAL DEVELOPMENT 3
2.1. Domain Theory 3
2.1.1. Uniting Management Accounting and Information Systems Frameworks 3
2.1.2. Evolving Role of Management Accountants 4
2.1.3. Contested Business Partner Ecosystem 5
2.1.4. Ambivalent Impact of Information Systems on Management Accountants 6
2.1.5. Emergence of Data Scientists 7
2.1.6. Research Questions 9
2.2. Method Theory 9
2.2.1. Katz & Kahn (1978): A Theory of Organizational Roles 9
2.2.2. Lado et al. (1997): A Classification of Interactions 12
2.2.3. Theoretical Framework 12
3. RESEARCH METHOD AND CASE BACKGROUND 14
3.1. Research Design 14
3.2. Data Collection 16
3.3. Data Analysis 16
3.4. Case Company 17
4. EMPIRICAL DATA AND ANALYSIS 20
4.1. Role of Data Scientists within the Case Company 20
4.1.1. Uncertain and High Expectations towards Data Scientists 20
4.1.2. Perceived and Occupied Roles of Data Scientists 21
4.2. Interactions between Data Scientists and Management Accountants 26
4.2.1. Task Monopolies of both Professions 26
4.2.2. Syncretic Interaction through Transfer of Data Science Models 28
4.2.3. Competitive Attitudes Triggered by Top Management 30
4.2.4. Collaborative Teamwork Resulting from low Role Ambiguity 32
5. CONCLUDING DISCUSSION 35
5.1. Data Scientists as a New Breed of Business Partner 35
5.2. Versatile Interactions Highly Influenced by Top Management 37
5.3. Outlook for Management Accounting 40
6. LIMITATIONS AND FURTHER RESEARCH 42
7. APPENDIX 43
7.1. Appendix A. Overview of Conducted Interviews 43
7.2. Appendix B. Excerpt of Question Catalog 44
7.3. Appendix C. Data Scientists' Role According to Katz & Kahn (1978) 44
7.4. Appendix D. Interactions According to Lado et al. (1997) 45
7.5. Appendix E. Task Comparison between Literature and Empirics 45
8. REFERENCES 46

1. INTRODUCTION

Information systems (IS) have constantly played an important role in enabling management accountants to fulfill their tasks (Rom & Rohde, 2007; Shields, 2001). Through the advancement of IT systems, the focus shifted from accelerating and improving the accuracy of traditional *Management Accounting (MA)* tasks towards the provision of sophisticated decision support (Mauldin & Ruchala, 1999). Over time, *Integrated Information Systems (IIS)*, especially in the form of *Enterprise Resource Planning (ERP)* systems, have become more prevalent, enabling central storage of information and a coherent generation of outputs throughout the organization (Davenport, 1998). In this context, the rise of *Business Intelligence & Analytics (BI&A)* systems is one of the latest trends within organizational systems that strengthens the link between the IIS and MA domains (Cokins, 2009; Maisel & Cokins, 2014; Rikhardsson & Yigitbasioglu, 2018). Rikhardsson & Yigitbasioglu (2018) define BI&A systems as decision-making support technologies that improve data collection, analysis and delivery of information results. It should be noted that *Business Intelligence (BI) systems* are based on semantically consistent data warehouses (Heudecker & White, 2014 quoted from Baškarada & Koronios, 2017), while *Analytics* make use of structured as well as unstructured data and apply i.a. statistical and predictive models for the generation of insights (e.g. Al-Htaybat & von Alberti-Alhtaybat, 2017; Davenport & Harris, 2007; Schneider et al., 2015; Trkman et al., 2010).

The advancing corporate importance of BI&A systems has been accompanied by two different views among MA researchers. On the one hand, authors such as Quattrone (2016) and McKinney Jr et al. (2017) argue for a cautious engagement with these new technological advances, as they might undermine the primary focus of Accounting, i.e. to support decision-making by initiating discussions and not to simply deliver results. On the other hand, especially practitioner-oriented literature proclaims that the access to more advanced systems and data sources enables management accountants to become business partners, by providing not only descriptive but also predictive or even prescriptive insights (Davenport, 2006; Holsapple et al., 2014). BI&A systems can find application in all Accounting tasks and are, thus, likely to become crucial enablers within management accountants' daily lives (Appelbaum et al., 2017). Surprisingly, even though the Accounting curriculum has not changed much since the mid-1980s (Pincus et al., 2017), the current literature is not adequately problematizing the shortcomings in the skill-set of current accountants (e.g. Appelbaum et al., 2017; Schneider et al., 2015). If management accountants do not have the skill-set to run BI&A systems, but these systems are likely to become enablers for MA tasks, then who is carrying out these tasks instead?

A hybrid professional (Zschech et al., 2018), the data scientist, has emerged as one of the most wanted jobs in the 21st century (Davenport & Patil, 2012). Clearly, this emergence is an example of how digitalization is "reshuffling the cards of companies' organization and structure while new cards are being introduced in the card deck" (Carillo, 2017, p. 602). Data scientists are viewed as the "missing piece of the big data puzzle" (Carillo, 2017, p. 607) and are already employed in many different functional areas (LaValle et al., 2011; Waller & Fawcett, 2013a), among others in Finance departments. Although research has been conducted on new players taking over MA tasks within the BI&A context (Arnaboldi et al., 2017), the MA literature has not yet analyzed this new player deriving from the IIS sphere.

In this paper, chapter 2 presents MA frameworks that combine both the IIS and the MA domains. We further give an overview of tasks that have been historically attributed to management accountants. Subsequently, these tasks are contrasted to those ascribed to the new professional actor, i.e. the data scientist. In this context, we present the research questions of this paper, that aim at closing significant research gaps in this area. Afterwards, method theories are introduced that enable the creation of a theoretical framework. Within chapter 3, the research method and case background are presented, so that the research questions can be analyzed in chapter 4 and, afterwards, discussed in chapter 5. Moreover, in this section a general outlook for the MA domain is given. Finally, the limitations of this study are stated and suggestions for further research are presented in chapter 6.

Although practitioner-oriented literature within MA mostly proposes that the management accountant is the benefiting individual from BI&A systems, this paper empirically assesses the role of data scientists and their interactions with management accountants. Thus, this paper contributes to MA literature in several ways. It not only answers calls for research on this topic (Baker & Andrew, 2019; Becker & Heinzelmann, 2017; Rickhardsson & Yigitbasioglu, 2018) but also embodies a polyadic analysis of the business partner ecosystem as opposed to the dyadic relationships investigated before (e.g. Byrne & Pierce, 2018; Llewellyn, 1998). Furthermore, the paper shifts the BI&A analysis away from a system-focus towards the individual sphere, i.e. from *Data Science (DS)* towards the data scientist.

2. THEORETICAL DEVELOPMENT

2.1. Domain Theory

2.1.1. Uniting Management Accounting and Information Systems Frameworks

Despite the advancing role of management accountants and the opportunities arising from new IS most frameworks not only from the MA domain, e.g. Simons (1994) and Merchant (1982), but also from the IIS domain do not include or only insufficiently cover the respective other domain. Therefore, these frameworks are neither adequate nor symbiotic enough (Mauldin & Ruchala, 1999; Rikhardsson & Yigitbasioglu, 2018; Rom & Rohde, 2007). To frame the domain of this paper we rely on the framework proposed by Rom & Rohde (2007), as it is based on an extensive literature review conducted on previous frameworks attempting to combine the IIS and MA domains, such as Mauldin & Ruchala (1999) and Vaassen et al. (2003). Compared to other frameworks, e.g. Appelbaum et al. (2017) or Rikhardsson & Yigitbasioglu (2018), which have a clearer system focus, Rom & Rohde (2007) take on a broader stance by developing a high-level overarching framework, including diverse organizational variables.

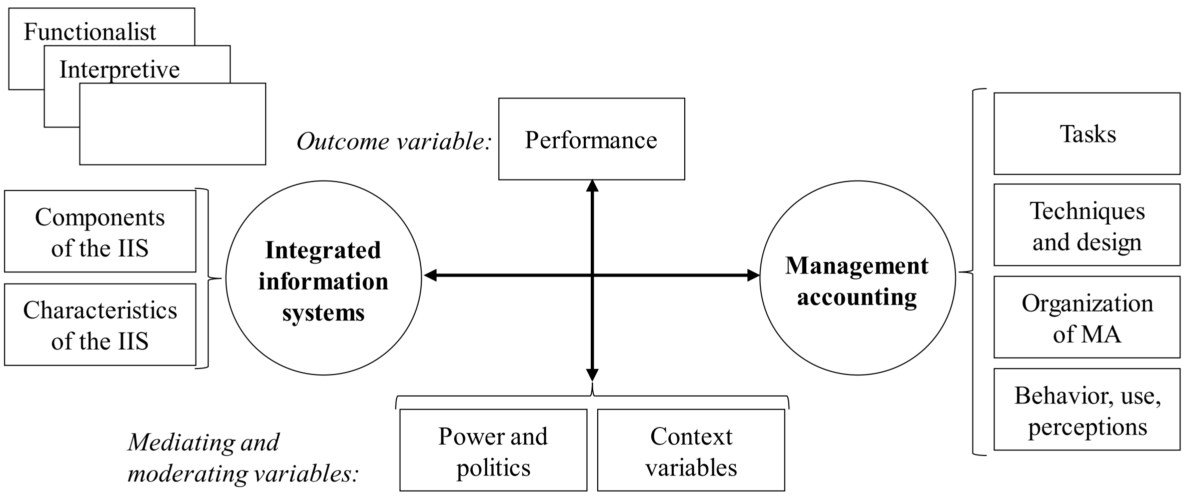


Figure 1. Theoretical Framework on IIS and MA Developed by Rom & Rohde (2007)

The Rom & Rohde (2007) framework, as illustrated in *figure 1*, argues for a decoupling of management accountants and MA tasks. It signifies that also other professions can carry out MA tasks and management accountants can engage in tasks outside their domain, such as IIS maintenance. Thus, it can be argued that the tasks of the MA domain are in constant motion. Similar to other components of their model, the relationship between the MA and IIS spheres is assumed to be bidirectional. This implies that not only changes in the MA sphere have an impact on the IIS sphere but also that changes with respect to the IIS are likely to impact management accountants and MA tasks. Rom & Rohde (2007) actively articulate that the framework can include other IIS systems than ERP systems that support MA. Even though BI&A systems are not explicitly part of the Rom & Rohde framework and literature review (Rikhardsson & Yigitbasioglu, 2018), we deem the framework still highly applicable due to its system independent and generic nature. Additionally, we will speak about IIS throughout the paper when referring to BI&A systems, since they are to the same extent as BI systems integrated with the organization's entire business information (Elbashir et al., 2011), enabling a central data access (Davenport, 1998; Gelinas et al., 2011; Granlund & Malmi, 2002).

2.1.2. Evolving Role of Management Accountants

The role of management accountants has evolved significantly over time and is nowadays often characterized as that of a business partner, who provides decision-relevant information to top management (Ezzamel & Burns, 2005; Goretzki et al., 2013; Goretzki & Messner, 2018; Järvenpää, 2007; Quattrone, 2016). Even though a more business-oriented focus is ascribed, the tasks of a management accountant can be divided into three main areas: cost accounting, the measurement of company performance and the provision of decision-relevant insights (Appelbaum et al., 2017; Cokins, 2013).

Cost accounting activities, which are interchangeably referred to as *financial reporting* in this paper, are shaped by regulatory compliance and are mostly manifested by the preparation of statutory accounts with a focus on external reporting (Appelbaum et al., 2017). The domain of cost accounting is perceived to be necessary, but of 'low value-add' for decision-makers within companies (Cokins, 2013). As the name suggests, *performance measurement* is about the assessment of historical performance (Appelbaum et al., 2017). According to Cokins (2013), related activities include e.g. variance analysis, process analysis or profitability reporting and can be classified as 'modest value-add' activities. The most advanced role of management accountants is providing *decision support with cost planning* (Cokins, 2013), which we will refer to as *business partnering* in this paper. Relevant information is provided to decision-makers (Busco et al., 2007; Hopper, 1980; Järvenpää, 2007; Sathe, 1983) by combining insights from financial reporting as well as performance measurement and enriching those with external data (Appelbaum et al., 2017). Further examples of business partnering include i.a. the calculation of customer lifetime values as well as process and productivity improvements and represent a 'high value-add' (Cokins, 2013). Other authors attribute tasks, such as the participation in decision-making and the consultation of managers (Granlund & Lukka, 1997, 1998), to the business partner role. *Figure 2* demonstrates the existence of direct linkages between BI&A systems and MA tasks (Appelbaum et al., 2017).

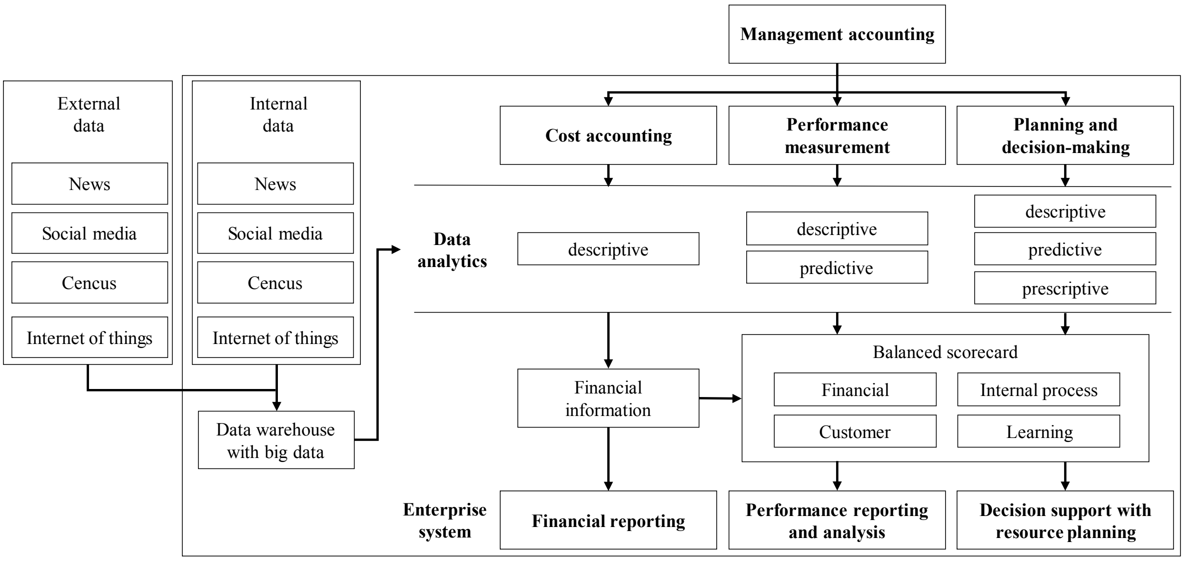


Figure 2. The Managerial Accounting Data Analytics (MADA) Framework, Developed by Appelbaum et al. (2017) and Motivated by Cokins (2013)

Based on these examples it becomes evident that the business partner role consists of rather abstract tasks instead of specific work packages (Siegel & Sorensen, 1999, Sorensen, 2009). In this context, management accountants have regularly been described as proactively influencing other professions, including managers, in order to take on these respective tasks (Goretzki et al., 2017). Since a growing 'partner or perish culture' (Goretzki et al., 2017) can be observed within organizations nowadays, not only management accountants but also other professionals perceive the pressure to perform these essential tasks. In this way, a competitive business partner ecosystem arises (Burns & Vaivio, 2001; Goretzki & Messner, 2018; Hunter et al., 2006; Mouritsen, 1996; Topinka, 2014) with different parties striving to accumulate prestigious strategic tasks while delegating so-called 'dirty work' (Hughes, 1951; Morales & Lambert, 2013) to other professions in order to gain organizational status.

2.1.3. Contested Business Partner Ecosystem

The literature on professions advocates to consider a broad organizational context when analyzing roles of and interactions between different professions (Anteby et al., 2016; Goretzki & Messner, 2018). Since research suggests that the role of the MA function is formed i.a. by the roles of other professional groups (Goretzki & Messner, 2018; Lambert & Sponem, 2012) as well as the organizational context (Lambert & Sponem, 2012; Morales & Lambert, 2013; Mouritsen, 1996), the following part summarizes the diverse means used by management accountants to establish themselves in the organizational arena.

Prior research on professional competition has shown that the (Management) Accounting profession has been highly successful at creating a superior professional ideology within organizations (Abbott, 1988; Armstrong, 1985; Richardson, 1988; Whittington &Whipp, 1992). The early foundation of professional bodies allowed that the (Management) Accounting profession became well-established within society, that it acquired political skills and enabled the conveyance of technological competence as well as ideological credibility (Whittington & Whipp, 1992). The rise was further facilitated by its technological superiority and by positioning itself to be the best-suited profession to tackle business problems (Armstrong, 1985; Whittington & Whipp, 1992). Technologies remained often only within the Accounting boundaries and, thus, were not accessible for outsiders in order to retain supremacy (Whittington & Whipp, 1992). An organizational decentralization of management accountants often enabled them to gain further knowledge through closer collaboration with Operations departments (Granlund & Lukka, 1998; Järvenpää, 2007). MA literature, furthermore, attributes the transformation towards a business partner and provider of truthful knowledge (Lambert & Pezet, 2011) to top management support (Järvenpää, 2007, 2009; Wolf et al., 2015) and the use of informational tactics, such as the creation of information asymmetries (Goretzki et al., 2018).

Nevertheless, the MA profession was not always capable of claiming the business partner role for itself. Although management accountants regularly benefitted from the previously mentioned means, scholars also report instances were management accountants lost the competition against e.g. Sales professionals (Vaivio, 1999) or buyers and merchandizers (Ezzamel & Burns, 2005). Both studies found that management accountants were defeated i.a. due to the lack of operational know-how. In the case of Ezzamel & Burns (2005), it led to a failed attempt of management accountants to impose controls on competing professions.

2.1.4. Ambivalent Impact of Information Systems on Management Accountants

With respect to the professional competition within IIS, authors like Sangster (1996) argue that management accountants can take on system responsibility and, thus, strengthen their status as well as role within organizations. Goretzki et al. (2013) find that management accountants assume a ‘gatekeeper’ role in the presence of an integrated ERP system, which, in turn, raises their internal importance. In line with this, authors, such as Caglio (2003), argue for a hybridization of tasks since the implementation of ERP systems was in many cases accompanied by management accountants’ task expansion into e.g. system maintenance (Becker & Heinzelmann, 2017; Caglio, 2003; Goretzki et al., 2013; Newman & Westrup, 2005; Rom & Rohde, 2007). But what impacts do BI&A systems have on management accountants and their tasks? We deem this question to be of high relevance since the hybridization and diffusion of Accounting knowledge as well as tasks have not consistently led to a gain of power. It also resulted in domain losses for management accountants (Jack & Kholeif, 2008; Newman & Westrup, 2005). By applying the 'technology power loop' on multiple case companies introducing ERP systems, Newman & Westrup (2005) show that the professional group gaining control over new technologies is able to positively shape its expertise and ultimately its organizational role. Recent literature shows that these findings also hold in the BI&A context. Arnaboldi et al. (2017) investigate BI&A systems and conclude that these systems enable individuals, traditionally outside the MA domain, such as Marketing and Communications managers, to claim performance management tasks from management accountants. This is a reversed example to Caglio (2003). In the empirical setting of Arnaboldi et al. (2017), the hybridization shifts the MA task sovereignty to these challenging professions. In the following, we introduce another profession that might have the potential of challenging the status quo of management accountants.

2.1.5. Emergence of Data Scientists

Since MA literature has not covered the data scientist yet, we rely on literature carried out by other domains in order to shed light on this almost 'mythical' profession (Baškarada & Koronios, 2017) within the MA context. A holistic definition is provided by Chatfield et al. (2014, p. 7), characterizing a *data scientist* as "someone who solves business problems by discovering patterns or trends in data, drawing insights from data and communicating these big data-driven insights to business decision-makers in a manner that they can understand the insights from big data". In order to develop an understanding of the relationship between management accountants and data scientists, *table 1* illustrates the tasks that both parties carry out. The table does not claim completeness and represents a rather aggregated view on the tasks of both professions in order to facilitate a comparison. At first glance, one can identify a significant overlap in tasks, both with respect to the system as well as the business sphere. According to practitioner-oriented research, data scientists perform tasks that can be associated with the area of performance management and business partnering as defined by Cokins (2013).

Table 1. A Comparison of Tasks of Management Accountants and Data Scientists

Task dimensions	Management accountants	Data scientists	Literature examples
System sphere (examples)	Implementation of systems [1]	Implementation of systems [2,3]	[1] Dai et al., 2013 quoted from Schneider et al., 2015 [2] Henke et al., 2018 [3] Power, 2016 [4] ISACA, 2014 quoted from Schneider et al., 2015 [5] Kim et al., 2016 [6] Davenport & Patil, 2012 [7] Brands & Holtzblatt, 2015 [8] Baškarada & Koronios, 2017 [9] Goretzki et al., 2013 [10] Becker & Heinzelmann, 2017 [11] Granville, 2014 [12] Cokins, 2013 [13] Appelbaum et al., 2017 [14] Patil, 2011 [15] Quattrone, 2016 [16] McKinney Jr et al., 2017 [17] Davenport, 2006 [18] Provost & Fawcett, 2013 [19] Carillo, 2017 [20] Braganza et al., 2017 [21] Mohanty et al., 2013
	Use of analytics tools [4]	Use of analytics tools [5,6]	
	Privacy and data security [7]	Privacy and data security [8]	
	Information gatekeeper [9,10]	Data management [11]	
Business sphere (examples)	Cost accounting / Financial reporting [12,19]		
	Performance measurement [12,13] ▪ Spending vs. budget variance analysis ▪ Profitability reporting	Performance measurement [14]	
	Business Partnering [12,15,16] ▪ Process improvement ▪ Customer lifetime value ▪ What-if-analysis ▪ Rolling financial forecasts ▪ Critics, informed skeptics	Business Partnering / Decision-making support [2,4,6,17,18,19,20,21] ▪ Process improvement ▪ Recommendation ▪ Insight generation and translation ▪ Visualization Experimentation and exploration of possibilities [6]	

The tasks carried out by data scientists, which are shown in *table 1*, necessitate a broad set of skills. Thus, data scientists are mostly seen as 'all-rounders' (Zschech et al., 2018). However, there is no real consensus on the required skill-set of data scientists (Mikalef et al., 2018; Schoenherr & Speier-Pero, 2015; Waller & Fawcett, 2013a). When aggregating the literature on the data scientist's skills four main areas can be identified, i.e. business knowledge, programming knowledge, statistical knowledge and soft skills (Carillo, 2017; Davenport & Patil, 2012; Granville, 2014; Mikalef et al., 2018; Mohanty et al., 2013). The soft skills mostly comprise communication and presentation skills. These skills would enable a data scientist to perform all of the above-mentioned tasks from understanding business problems, coding models, communicating results to decision-makers and implementing models into the systems afterwards. However, due to the extensive as well as interdisciplinary skill requirements, many people question whether one individual can incorporate all required skills (Carillo, 2017; Waller & Fawcett, 2013b). Thus, a data scientist is also regarded as a 'five-legged sheep' (Carillo, 2015).

2.1.6. Research Questions

Since mostly practitioner-oriented research outside the MA domain suggests that data scientists perform MA tasks and, moreover, that data scientists may have the necessary skill-set to carry out these tasks we strive to empirically investigate the following *research question (RQ)* for the first time, to the best of our knowledge, within the MA domain.

RQ1: What is the data scientist's role and does it coincide with that of a management accountant?

We show empirically to what degree this new party has already taken over core MA tasks. Overall, a more elaborated face is given to the data scientist within the MA context and the profession is put in the spotlight for further research within MA. In the next chapter, the relevant parts of the social-psychological framework developed by Katz & Kahn (1978) are described, which are used to assess the role of the data scientist within the MA context.

While the first question investigates whether there is an overlap of roles between management accountants and data scientists or not, RQ2 focuses on the interactions between data scientists and management accountants. Similarly to RQ1, this phenomenon has not been empirically studied. Therefore, our second RQ is:

RQ2: How do data scientists interact with management accountants?

With this RQ we work towards the research gap identified by Becker & Heinzelmann (2017), who suggest investigating inter-professional conflicts over jurisdictions (Abbott, 1988), responsibilities and accountabilities between the aforementioned parties. We take on a broader stance within both RQs and extend the analysis beyond a dyadic relationship towards a polyadic perspective by taking into account several other organizational parties.

2.2. Method Theory

In the following sections, the applied method theories to answer the RQs are described and, subsequently, linked to the MA and IIS domains via a theoretical framework.

2.2.1. Katz & Kahn (1978): A Theory of Organizational Roles

The second edition of the book 'The Social Psychology of Organizations' written by Daniel Katz and Robert L. Kahn was published in 1978. The authors refer to the organization as an open system of roles, where a *role* is characterized by the abstraction of essential recurring features from the specific activities that comprise the *role behavior*. These specific activities include tasks as well as interactions and are based on the individual's skill-set and personality. By these means one can speak of the role of a person in general terms without specifying her or his tasks in detail.

Each human action is, first, influenced by other individuals and, subsequently, impacts others. Thereby, individuals can be located according to their relationships to others and to the system as a whole within the organization. This relational concept is called *office.* The sum of all offices that are connected to a single office constitutes the *role-set* (Merton, 1957 quoted from Katz & Kahn, 1978). In organizations, these are mostly colleagues of adjacent workflow processes and the hierarchy of authority, i.e. the immediate superior and subordinates. On the one hand, members of the role-set have expectations about the behavior of a specific person holding an office, called *focal person*. On the other hand, the focal person's behavior influences the expectations of the role-set. The entirety of these two interdependent processes is labeled as one *role episode*. In the following, the Katz & Kahn (1978) framework, which is presented in *figure 3*, is described in detail. First, the specific stages of the role episode are covered. Subsequently, the contextual impact on the role episode is highlighted and real-life complications are presented.

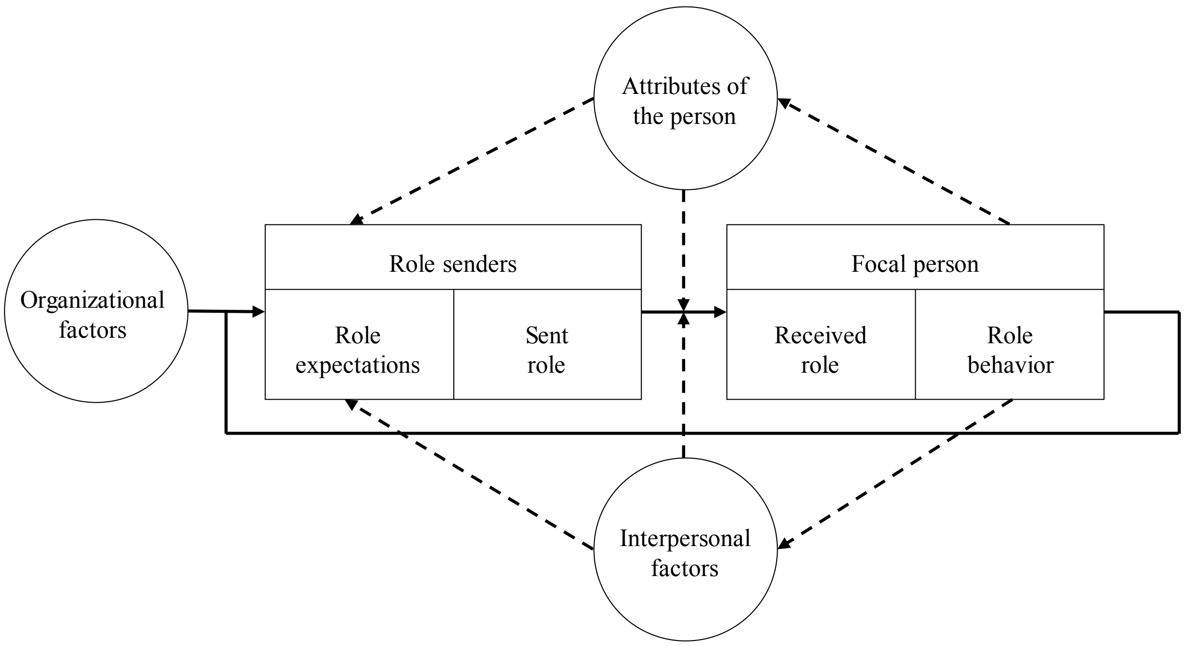


Figure 3. The Theoretical Model of Factors Involved in the Taking of Organizational Roles Developed by Katz & Kahn (1978)

The process of role-sending starts in the mind of the individuals that form the role-set. People have specific expectations about the focal person's role. This means that a person develops ideas and opinions about what the focal person should or should not do as part of the associated role. We define this conviction as the *perceived role*. Although expectations are merely a cognitive construct, the ideas do not remain in the mind of members of the role-set but are transmitted to the focal person. The communicated role is referred to as the *sent role*. In order to examine how the focal person interprets the role that was addressed by role-senders, the individual's perspective is required. Since the perception differs among individuals due to personal, organizational and environmental factors, there is not only a sent role but also a *received role*. Subsequently, the type of received role directly impacts the focal person's role behavior as well as the ambition to comply with the expected performance. We label the role behavior within the organization as the *occupied role*.

While the focal person performs the role behavior in interaction with the role-set, a feedback loop emerges. Members of the role-set assess to what extent the focal person's behavior complies with their initial role expectations. In case the focal person's role behavior corresponds to the role expectations of the role-set, role-senders' expectations about the focal person's role are reinforced. On the contrary, if the focal person does not meet the role-senders' expectation, role-senders will adapt their ideas and beliefs about the focal person's role. As a consequence, the information gained by the role-senders through assessing the degree of compliance of the focal person's role behavior to their expectations in a continuous manner will affect the ensuing role episode. The above described cyclic, ongoing design of the role-sending and feedback process does not take place in isolation. It is rather influenced by several contextual factors. Organizational factors, such as formal policies, technologies used, and the organizational structure have a direct impact on the role-set's expectations. The cause of and effect on personal as well as interpersonal attributes has been neglected in this study.

The theoretical concept developed by Katz & Kahn (1978) allows to illustrate disputes that can occur within the role episode. In general, the uncertainty about the focal person's task responsibility represents *role ambiguity*. Additional ambiguity concerning other aspects of the role includes the type of final output required by the role-set and the assessment criteria of present role behavior. The concurrent existence of two or more diverging role expectations of a single role defines a *role conflict*. It implies that the compliance with one role expectation would contradict the adherence to another role expectation. The focal person's decision of not enacting a certain role and, thereby, opposing the role-set's expectation of behavior and implying the need to take an alternative action is defined as *role distancing*. In case role-senders are not able to communicate any or only vague expectations, we label this part of role distancing as *role making*.

2.2.2. Lado et al. (1997): A Classification of Interactions

At the same time, we aspire to expand this paper from analyzing the role towards understanding the interactions of organizational groups. Lado et al. (1997) created a four-cell typology that enables to study interactions in a more granular way than by characterizing interplays as either cooperation or competition. This is done by incorporating aspects of game theory, resource-based theory and socio-economics. Even though the authors established this model to assess interactions between entities, we deem it adequate to be applied in an organizational setting and, thus, to analyze interactions of professional groups.

		Competitive Orientation: Low	Competitive Orientation: High
Cooperative Orientation	High	Collaborative Rent-Seeking Behavior	Syncretic Rent-Seeking Behavior
	Low	Monopolistic Rent-Seeking Behavior	Competitive Rent-Seeking Behavior

Figure 4. The Syncretic Model of Rent-Seeking Strategic Behavior by Lado et al. (1997)

Figure 4 illustrates the potential forms of interactions. An interplay can be classified as *collaborative* in case parties exhibit a high degree of collaboration and overcome a competitive orientation in order to achieve beneficial effects by complementing each other's capabilities (Lado et al., 1997). A *syncretic* relationship is characterized as a balance between highly competitive and highly collaborative behavior, which enables parties to leverage their competencies and create growth beyond the impact of either collaborative or competitive strategies (Hamel et al., 1989; Lado et al., 1997; Ohmae, 1989; Pucik, 1988). In contrast to that, a low competitive and low cooperative orientation constitutes a *monopolistic* behavior. This is achieved if one party can prevent others from entering its domain of action (e.g. Buchanan, 1980; Porter, 1980). A party that is following a *competitive* behavior does not prevent others from entering the domain but rather strives to create favorable circumstances for itself in order to achieve a position of superiority and competitive advantage. This is often achieved by creating unique competencies (e.g. Barney, 1991; Conner, 1991; Lado et al., 1997).

2.2.3. Theoretical Framework

MA scholars have, thus far, and to the best of our knowledge mostly studied the impact of BI&A on the management accountant's role from a system perspective (e.g. Appelbaum et al., 2017; Rikhardsson & Yigitbasioglu, 2018). Only a few studies have assessed jurisdictional conflicts with already established organizational actors, such as Marketing and Communications managers (Arnaboldi et al., 2017). Within RQ1 we, thus, strive to scrutinize the role of the data scientist to extend the BI&A discussion towards this new organizational player. In this context, the discussion about the decoupling of management accountants and MA tasks (Rom & Rohde, 2007) is extended by assessing to what degree the data scientist's role coincides with that of a management accountant. The theoretical model of Katz & Kahn (1978) allows us to assess the role of the data scientist, who becomes the focal person of this study, while management accountants and other professionals act as role-senders. We acknowledge that our aim is not to capture the role of the data scientist in its entirety through the Katz & Kahn (1978) framework. Instead, we rather intensify the focus on MA-related tasks (e.g. Appelbaum et al., 2017; Cokins, 2013). Furthermore, we customize the framework of Katz & Kahn (1978) to some extent. We do not assess the roles that are specific to individuals but rather assume that there are uniform roles within each department. Thus, we adapt the framework from assessing the role of focal persons to rather analyzing the role of focal teams. With regards to the contextual variables, we focus primarily on organizational factors and neglect personal as well as interpersonal factors. This is because we did not conduct first-hand observations of interactions between data scientists and management accountants or other professionals.

After determining the actual overlap of tasks between both parties, RQ2 assesses how data scientists and management accountants interact and whether one party dominates traditional MA tasks (Abbott, 1988; Becker & Heinzelmann, 2017; Rickhardsson & Yigitbasioglu, 2018). We contribute to MA research, not only by assessing these new interactions between data scientists and management accountants but also by providing a further study going beyond a dyadic investigation (e.g. Byrne & Pierce, 2018; Llewellyn, 1998). Analyzing the interactions in accordance with Lado et al. (1997) allows us to examine the current power dynamics in a nuanced way and to find means applied by both focus professions to shape the relationship. Both analyses are carried out within a broader role-set, i.e. a polyadic ecosystem consisting of management accountants, data scientists, top managers and professionals from the Actuary, IT and Operations departments.

3. RESEARCH METHOD AND CASE BACKGROUND

This chapter describes the research design of this study and outlines the process of data collection as well as data analysis. Subsequently, the setting of the case company is introduced.

3.1. Research Design

We conducted a qualitative case study in order to investigate the RQs raised above. Ridder (2017, p. 282) argues that "case study research scientifically investigates real-life phenomena in-depth and within the environmental context". In our study, the real-life phenomena to be investigated are the data scientist's role through Katz & Kahn (1978) as well as the interactions between data scientists and management accountants in accordance with Lado et al. (1997). The case company has not been chosen in order to be fully representative for an overall population but rather because the case is of interest (Stake, 2005). The organization has different business segments, which independently created DS departments at different points in time. The organizational characteristics of the case company act as the environmental context. Since we investigate the phenomena within one particular organization, we conduct a single case study (Yin, 1994). By being restricted to one industry and carrying out interviews in only one country, the contextual variables are highly comparable across all business segments. In the eyes of Dyer Jr & Wilkins (1991) a significant trade-off between the benefit of comparisons across cases and the in-depth understanding of a setting can be found. Since the field of research is nascent, we favor a single case study in order to scrutinize the phenomena in more depth.

Prior research about the impact of DS on MA has largely focused on systems (e.g. Appelbaum et al., 2017; Rikhardsson & Yigitbasioglu, 2018). The primary unit of analysis in this study is the role of the individual. The unit of analysis used is not entirely new within the MA domain, since the individual role of the management accountant has already been established, e.g. through Byrne & Pierce (2018). It is, however, new to MA that the focal person is the data scientist, i.e. a person from outside MA. Concentrating on the individual corresponds to the method theory as the framework developed by Katz & Kahn (1978) focuses on the cognitive processes of a singular person. Nevertheless, the research design did not refer to the role of and interaction with individual members by itself, but rather focuses on the expectations of and collaborations with focal departments. This allows us to make better comparisons across interviews since we are able to compare expectations that are held in general of someone working within a specific department. Interviewing three different business segments corresponds to an embedded unit of analysis (Yin, 1994). We decided to study multiple teams in order to get enough empirical data to answer the RQs with high reliability. With this approach, opportunities for extensive analysis are created (Yin, 1994). We analyze the data not only within segments but also draw differences and similarities across segments and cancel out individual biases (Baxter & Jack, 2008; Stake, 1995).

In this study, the opinions of the interviewees are only analyzed at a single point in time. This allows us to compare primarily the status quo. We acknowledge that the framework provided by Katz & Kahn (1978) is dynamic in nature, impacting expectations and the type of interaction over time. The role expectations of a person either strengthen or change through a confirming or disconfirming feedback loop described by Katz & Kahn (1978). The analysis of the feedback loop would require a longitudinal study first and foremost. Although this study is cross-sectional (Ridder, 2017) in nature, the different maturities of the DS departments within a comparable organizational setting allow us to draw longitudinal conclusions to a certain degree.

Ridder (2017) examines four general designs of case study research. Since the intersection of MA and IIS has already been explored in the past (e.g. Mauldin & Ruchala, 1999; Rom & Rohde, 2007; Vaassen et al., 2003) and, on a more granular level, the impact of BI&A systems on MA has been scrutinized (e.g. Appelbaum et al., 2017), there are already established theories in this field. However, we observe that the data scientist's role in MA has not been investigated yet (e.g. Rickhardsson & Yigitbasioglu, 2018). Consequently, our case study is designed according to the approach developed by Yin (1994). It takes the existing framework of Rom & Rohde (2007) as a starting point and defines the RQs as the identified gaps within the literature. This open-ended research design complies with the classification by Edmondson & McManus (2007) as the literature about the role of the data scientist as well as the interactions with management accountants is rather nascent. The results can be seen as an invitation for further research (Edmondson & McManus, 2007) by calling attention to this blank spot in the MA literature. On an individual basis, the analyses of both RQ1 and RQ2 are of illustrative nature, i.e. being described more in detail. This is because no research has investigated the phenomena yet, thus, they need to be introduced to the reader comprehensively (Edmondson & McManus, 2007). The reader should understand the phenomena through a lively experience of a real setting in its entire complexity (Lincoln & Guba, 1985) to create a déjà vu effect when the reader investigates similar situations in the future (Langley, 1999). Comparisons are drawn to existing literature which has already covered the role of the management accountant and the role of the data scientist outside MA literature.

3.2. Data Collection

The data used to analyze the phenomena were primarily compiled via semi-structured interviews with individuals. Edmondson & McManus (2007, p. 1162) argue that interviews, among others, are "methods for learning with an open mind" and help researchers to determine as well as scrutinize key variables. Since the RQs are considerably open-ended, this approach shaped our study along the way. Interviewing individuals is clearly linked to the method theory (Katz & Kahn, 1978) because the role expectations of individuals are the core of this study. The primary source of data was complemented with secondary sources, such as job advertisements that were relevant to the studied phenomena (Edmondson & McManus, 2007). Interactions between the DS and other departments, however, could not be directly observed.

In total, 20 interviews were conducted with 23 individuals. 22 employees were interviewed in person. Seven of these were met in location 1 in February 2019 and fifteen in location 2 in March 2019. Additionally, one individual was interviewed over the phone in March 2019. A break of two weeks between the sites was scheduled to analyze the first interviews and retain enough flexibility to reconsider the approach. During the interviews, one researcher was in charge of conducting the interview, while the other focused on taking notes and raising open-minded follow-up questions. All interviews were recorded and subsequently transcribed. On a departmental level, nine interviewees were from MA departments, eight from DS departments and the remaining six from other departments, i.e. Actuary, IT and Operations. At least two individuals were predominantly interviewed from within a single department in order to avoid a selection bias (Byrne & Pierce, 2018). Pseudonyms were assigned to the company as well as to the individuals in order to establish trust with the interviewees and to respect confidentiality and discretion. Please refer to *Appendix A* for more information.

Yin (1994) writes that propositions are necessary in order to identify the relevant information instead of being tempted to every detail. Although we strove to remain flexible in pursuance of exploring interesting topics, we created a question catalog beforehand, which would guide the interview to some extent. Each interview was divided into three parts and adjusted to the respective department, i.e. DS, MA, and other departments. Please see *Appendix B* for an exemplary question catalog.

3.3. Data Analysis

After every interview as well as after the entire interview day we discussed the overall findings in order to adapt the question catalog. Thus, the data collection and data analysis iterated continuously to reveal new topics of interest via thematic content analysis (Edmondson & McManus, 2007) and to explore these new topics in further detail during subsequent interviews. It was crucial to learn from each new interview and recognize key insights, commonalities and differences to other interviews. The iteration between data collection and data analysis was also needed due to the nascent type of literature on the investigated phenomena as key constructs had not been established by literature in advance (Edmondson & McManus, 2007). Consequently, the interviews were re-read again, and the important findings were translated. The translation required a process of sensemaking due to linguistic and sociocultural differences between the interview language, i.e. German, and English (Huiping, 2008). Subsequently, the translated statements were mapped in a matrix. The visual mapping strategy allowed the comparison of large quantities of information (Langley, 1999). For RQ1 the matrix contained columns for the individual processes of the Katz & Kahn framework (1978) and for RQ2 it contained a column for each type of interaction described by Lado et al. (1997). In the rows the interviews were added over time. In each column general topics emerged that allowed to classify insights even more granularly. The inclusion of stories in the matrix which is part of the narrative strategy (Langley, 1999) helped to achieve a thick level of description later and, thus, increased transferability (Lincoln & Guba, 1985). This way the most relevant patterns not only within teams but also across teams could be identified (Ridder, 2017).

After the completion of all interviews, the observed patterns were triangulated (Eisenhardt, 1989) with secondary data sources to get a full picture of the empirics. This process further enhanced the credibility of the findings (Lincoln & Guba, 1985). Thereafter, the empirical findings of both RQ1 and RQ2 were compared to the literature on the studied topics (Baxter & Jack, 2008; Eisenhardt, 1989).

3.4. Case Company

The German corporation, *InsurCo*, is a major player within the insurance market and provides a broad range of insurance products to its clients ranging from health, life to property insurances. The insurance industry is regulated to a large extent in Germany and remains highly administrative up to this day. Therefore, laws on data security as well as privacy are strong, and the works council has significant influence. Within our analysis, we focused on three different segments within InsurCo, outlined in *figure 5*, that have independently created DS departments over time, i.e. Market management (*Market*), Health insurance (*Health*) and Life insurance (*Life*). The Market team is located above the individual insurance segments. It takes a holistic view of the client, tries to identify cross-selling opportunities among segments, integrates the distinctive insurance segments and plans marketing initiatives. This unit is located together with the Health insurance business in location 2. The Health segment provides health insurance cover to patients within Germany. Their data are stored rather centrally as opposed to the Life insurance segment, which is based in location 1. Within Life data are highly fragmented throughout the organization.

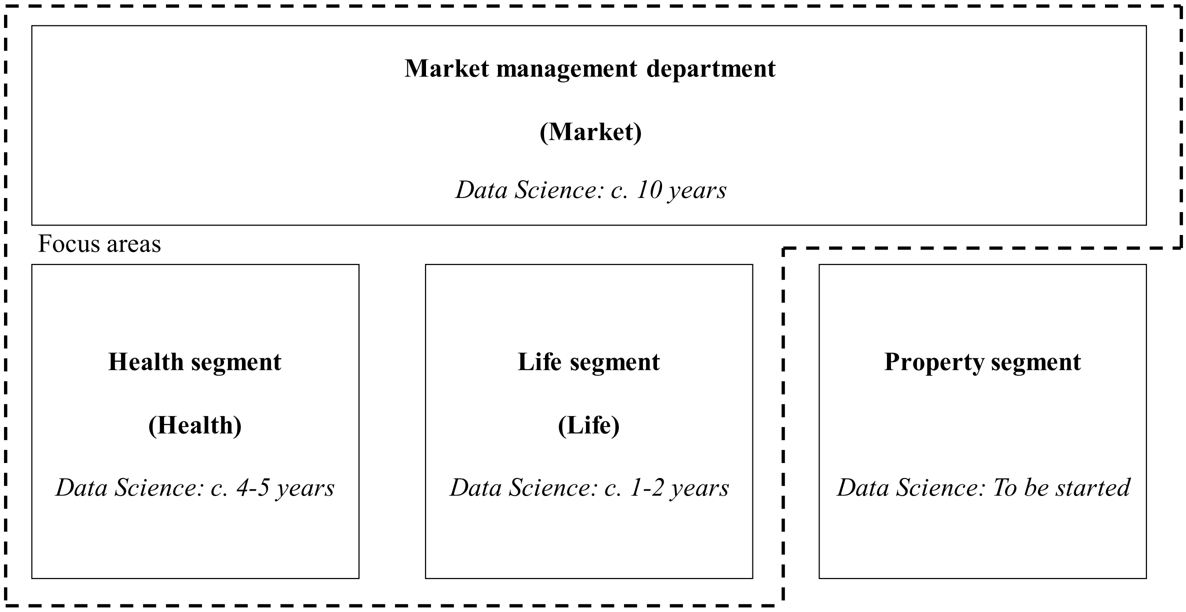


Figure 5. The Analyzed Organizational Context of InsurCo

Since the case company has been operating for more than a century, the IT landscape is relatively complex and consists of different legacy systems. *Figure 6* depicts a simplification of the integrated data and system landscape of the case company. The most rudimental database within the organization is called *raw basis layer* and includes insurance policy information of all contracts and other basic data of InsurCo. These data are then, on the one hand, used to operate the ERP system with the main purpose of conducting statutory reporting and, on the other hand, used for BI&A purposes. A duplication of the raw basis layer constitutes the *BI basis layer*, which in turn serves as the source for different segments and functions of InsurCo to aggregate data with distinct business logic in so-called *cubes* or *data marts*. Data integrity and allocation of responsibilities is ensured by a BI governance board.

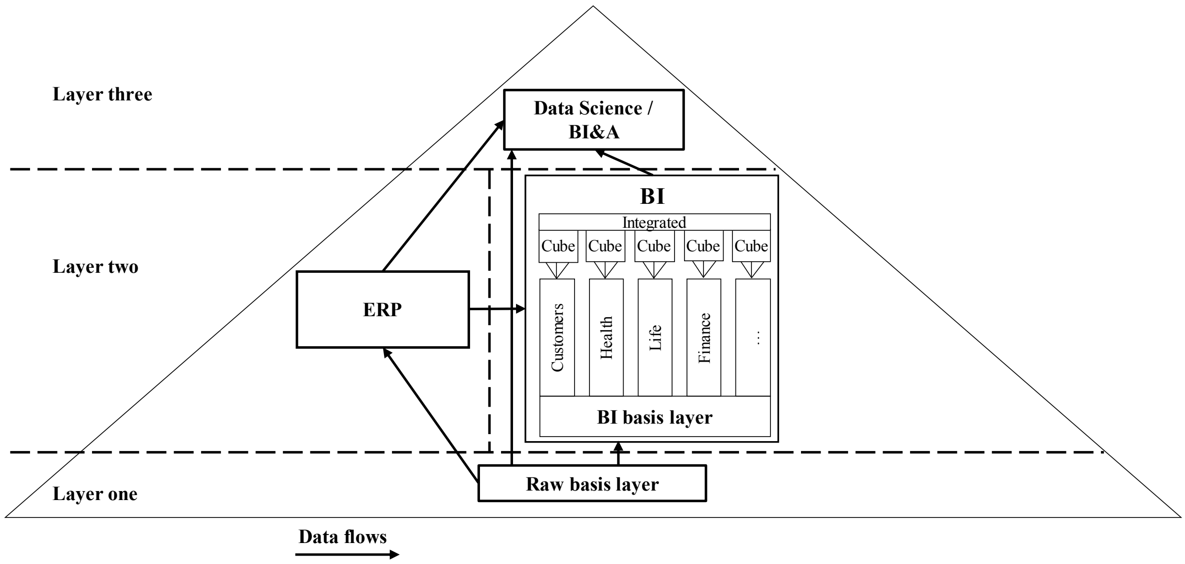


Figure 6. The System Landscape of InsurCo

The MA department within InsurCo is to some extent standardized but also adjusted to the individual needs of the respective segment. The standardized part comprises of the Cost Controlling, i.e. primary costs and corporate costs, and is taken care of in a similarly structured department within each segment to ensure comparability, exchange of information and better cost allocation across segments. These tasks mainly serve financial reporting purposes. The customized part of MA is not constrained to only a single MA department, but is rather decentralized, i.e. distributed throughout the organization. While these departments take on supporting functions for reporting tasks, they are most active in the area of performance measurement including the presentation of results to decision-makers as well as traditional business planning.

Opposed to the long tradition of MA within InsurCo, the DS departments only emerged recently. Within Market, the DS team has existed for approximately ten years, whereas in the Health and Life insurance segments they were created four years and 18 months ago, respectively. The DS teams within Market and Health arose from internal units, whereas the team within the Life insurance business was mostly staffed externally. In total, roughly 20 data scientists are employed within the three segments. On the organizational chart, the DS departments are directly located under the board of directors of the respective segment, i.e. a board member is directly responsible for the DS department. This is done purposely to highlight the strategic importance of these departments within the organization. Another organizational aspect is the cost allocation of the data scientists. To our understanding, especially the costs of the DS teams in the Health and Life segments are not allocated, which, according to InsurCo representatives, is a way of promoting DS within the company.

4. EMPIRICAL DATA AND ANALYSIS

Within the introduced setting, the RQs are investigated in the following. The analysis is divided into two separate parts, i.e. each respective RQ.

4.1. Role of Data Scientists within the Case Company

In this chapter, the framework of Katz & Kahn (1978) is applied in order to assess the role of the data scientist as raised under RQ1. First, the role ambiguity, including the degree of diverging expectations is analyzed. Subsequently, the perceived as well as occupied role of data scientists within InsurCo and the arising role conflicts are investigated.

4.1.1. Uncertain and High Expectations towards Data Scientists

The uncertainty about the actual role of a data scientist is called role ambiguity. In total, eight of fifteen role-senders have difficulties to define the actual role and to articulate tasks of data scientists. It is partly acknowledged that the whole company "does not know yet how to bring them [data scientists] into the organization and combine them with the departments' know-how" (IP5, Manager Management Accounting, Life). For a management accountant that already performs predictions based on advanced models, the distinction between a management accountant and a data scientist is highly unclear.

> For me, it is hard to separate and to say, 'there is a data scientist who generates insights based on data', while it is the same within Management Accounting. Ultimately, we also dig down to the individual commissions and damages and have the skills and the curriculum for data analysis. (IP16, Management accountant, Health)

It may be difficult to differentiate these roles because tasks that both parties perform, such as 'data analysis', on an abstract level appear to be homogeneous based on the vocabulary, although they differ contextually. Not only the distinction is unclear to role-senders. It seems that the entire workflow of insight generation is comparable to a black box for role-senders, which makes individuals doubt the results data scientists generate. This highlights the risk of making "people take wrong decisions much more quickly" as identified by Quattrone (2016, p. 120).

> It is a little bit bad that sometimes one does not know what they are doing with our data and how they do it. Therefore, the question: Are the conclusions they draw actually the conclusions we would draw? (IP6, Management accountant, Life)

The prevalent role ambiguity of role-senders was confirmed after the first interaction with data scientists. When asked about the first results data scientists provided, some role-senders felt that they "did not receive, what was expected, but less" (IP7, Manager Management Accounting, Life) and that they "were disappointed, because there was nothing new" (IP6, Management accountant, Life). Within segments that have more mature DS departments, i.e. Health and Market, a change in expectations has already been realized. Now, more realistic expectations can be observed within both, role-senders and role-receivers. A management accountant identifies that DS "has its limits because data are data" (IP14, Manager Management Accounting, Health). However, data scientists state that "it was a difficult process" (IP10, Data scientist, Health) to manage expectations down.

Despite the tendency towards more realistic expectations, one can observe that the overall level of expectations that role-senders have towards data scientists remains predominantly high. Role-senders require data scientists to "answer questions that have not been asked yet" (IP3, Manager Operations, Life) or to "teach [them] something about the business area (…) [they] did not know before" (IP7, Manager Management Accounting, Life). Role-receivers clearly notice these high expectations of role-senders. "It is somehow expecting magic" (IP1, Data scientist, Life) as if they "could save the world by employing data scientists tomorrow" (IP17, Manager Data Science, Market). Role-receivers, however, emphasize that "it is no crystal ball" and that they are no "wizards" (IP12, Data scientist, Market). Sometimes the targets require something "that the data and the business model (…) do not constitute" (IP9, Data scientist, Market).

4.1.2. Perceived and Occupied Roles of Data Scientists

This chapter combines the thoughts of both role-senders and role-receivers to establish and analyze the perceived and occupied role of data scientists within InsurCo. Since a role is an abstraction (Katz & Kahn, 1978) we compare the expectations on the data scientist's role, specific tasks and skills.

Role-senders unanimously regard a data scientist as a consultant or translator, because the data scientist "has to be able to consult concerning the question: How do I translate a business problem into an analytical problem?" (IP22, Manager IT). In some instances, the data scientist is seen as an initiator or enabler in the eyes of role-senders. There is a partial overlap with the data scientists' view on themselves. They clearly see themselves as "an initiator or maybe as the creative part" (IP23, Manager Data Science, Health) while some individuals agree with role-senders and speak of being enablers and consultants, since they "enable other departments with their growth topics and deliver added value. This is our [the data scientists'] main reason for existence" (IP8, Manager Data Science, Health). Since roles and definitions are too general to draw a detailed conclusion, we further analyze which type of work a data scientist performs both on a general level and whether he or she takes on traditional MA tasks as defined by Cokins (2013). On a general basis, the following quote represents which tasks role-senders expect from a data scientist.

> As a data scientist I would expect someone, who is capable of reflecting which data are required, understanding the data with help of the data owner, instructing how to clean and process the data so that they can be used for analysis and prognosis, describing the respective model, building the model, evaluating the results, running clean tests concerning model quality and then, in the end, monitoring the implementation into the system. (IP11, Manager Management Accounting, Health)

The translation process and the application of statistical and DS methods are undisputed by both parties. These findings are in line with previous literature (Davenport, 2006; Davenport & Patil, 2012; Kim et al., 2016). Data scientists believe that DS creates value by either "improving as well as automatizing processes or generating insights, which lead to making better decisions" (IP17, Manager Data Science, Market). One can observe that depending on the maturity of the DS department the task focus moves away from automatization to insight-generation once the benefit of further automatization become only marginal.

The optimization of processes is a key example of experimentation and exploitation of DS possibilities (Davenport & Patil, 2012). This finding corresponds to the job description of data scientists which includes to "identify new business potentials" (InsurCo job advertisement). The task of developing insights is a clear execution of decision-making support (Davenport, 2006) and corresponds to the role of a business partner (Cokins, 2013; Goretzki & Messner, 2018; Hunter et al., 2006; Topinka, 2014). We believe that insights can be either the confirmation of already known phenomena or the discovery of unknown relationships. Data scientists express that they "need to provide results beyond the obvious. If the results and the model prove that the assumption is correct, (…) that is nice, but we have not shown that we are better" (IP1, Data scientist, Life). Role-senders agree that data scientists should create insights, but they are not aligned on the type of insight to be generated. Some role-senders expect data scientists to create new insights, while others also appreciate the confirmation of already known ideas.

> If this work is already performed in a different way in the company and we have the insight, then we don't need them. (…) It is like if someone tells you after two years of research: 'The earth is round'. That is nice to hear, but we know it already. Tell me something new. (IP6, Management accountant, Life)

> Even though some other people might not agree, it is a success if an idea I had before is confirmed by those methods. Some might see that as a failure, but I would say that I

> finally have clarity about it and that is a valuable insight. (IP5, Manager Management Accounting, Life)

A clear role conflict between role-senders and role-receivers arises when looking at whether data scientists should give recommendations to decision-makers or not. Data scientists clearly believe that it is part of their job. This is further substantiated by literature (Kim et al., 2016) and the job advertisement for a data science position within InsurCo. The role includes to "support decision-making" and the chosen individual would "independently interpret the results (…) and discuss them with top management" (InsurCo job advertisement).

> The value creation is not completed by doing a sophisticated analysis. (…) Not like 'this is my result, do something with it' but rather that I clearly formulate it [the recommendation]. (…) You miss out a lot if this does not happen. (…) Another person receives it [the analysis], has his or her own ideas and goes another way. (IP17, Manager Data science, Market)

Role-senders have an inconsistent view on this topic. There are three different manifestations. Some management accountants believe that data scientists do "not have enough capacity to dig down within the content to give more than general recommendations" (IP11, Manager Management Accounting, Health). Others are cautious and feel that data scientists should be allowed to give recommendations "if they can do it themselves" (IP14, Manager Management Accounting, Health). Actuarial employees, on the other hand, are convinced that the person "who knows the data best is most suitable to give recommendations for action" (IP13, Manager Actuary, Health).

Moreover, the question of whether and to whom data scientists should present the results does correspond neither between role-senders, nor role-receivers. Even management accountants do not agree with each other whether data scientists should report directly to the board. Some management accountants see the risk of a "filtering process" (IP6, Management accountant, Life) when data scientists report findings to the business and not directly to the board. In this case, the findings of the independent data scientist may already be disapproved by the affected individuals before reaching the board. Others feel uncertain whether data scientists are capable of preparing the findings on a holistic level as the following quote illustrates.

> I am unsure. (…) Are they capable of preparing the findings in a holistic way? If they are, why shouldn't they do it? But I don't think so. Then they are no more data scientists, but business experts. (IP11, Manager Management Accounting, Health)

Data scientists, nevertheless, distance themselves from these expectations as they already communicate their findings to all levels. One method employed by data scientists to convey the message to management is the utilization of key performance indicators (KPIs). The job advertisement for a senior data scientist position within InsurCo clearly states that it is the person's task to "measure and track the impact of the products developed through business KPIs" (InsurCo job advertisement). We observed this also within our interviews where data scientists proactively develop KPIs to measure results. The following quote confirms previous literature that data scientists engage in performance measurement (Patil, 2011) and, consequently, carry out a traditional MA task (Cokins, 2013; Simons, 1994).

> We are working on defining our measures. How do we define the KPIs for each project? (…) We are striving to find a KPI for each of the outcomes of the projects. (IP1, Data scientist, Life)

Data scientists within InsurCo, however, exceed the tasks provided in the existing literature. They express that their responsibility is to make the company more data-driven, both within the system and business sphere. On the system side, data scientists try to enhance the digital infrastructure. They see themselves as the "leader in aggregating data" (IP17, Manager Data Science, Market), because it is of their interest to have a consistent view throughout the entire organization. Through this process, they have access to all data layers (see *figure 6*), thus, they become a party that has a holistic view of all company data. On the business side, their aim is to develop a digital mindset within the entire organization. Since the knowledge about DS is nascent within the company, a big part of data scientists' work is to "educate, build awareness and create realistic expectations" (IP17, Manager Data Science, Market).

> Currently we support the board by identifying obstacles and issues that prevent us from getting there [becoming digital native] faster. (…) This is one of the roles that we have to integrate into our daily job. We change a bit the mindset of people here. (...) It is the final goal to reach a changed mindset in a couple of years. (IP1, Data scientist, Life)

Managing expectations and establishing a digital mindset can be considered as proactive steps of role making and are clear implications of the high role ambiguity of role-senders due to no or at most vague expectations. Without a clear set of role expectations, role-receivers are not able to passively react upon the role-senders' provisions but need to influence role-senders' expectations proactively. Role-senders' belief that data scientists also "take care of the technical implementation" (IP13, Manager Actuary, Health; IP11, Manager Management Accounting, Health) of developed models is in line with previous literature (Henke et al., 2018; Power, 2016). Within InsurCo, however, role-receivers point out that the IT department oversees the implementation (IP17, Manager Data Science, Market). This division of labor between the DS and IT department is not in line with previous research and can be interpreted as a way to rather focus on DS methods as well as the high amount of business cases they work on. Moreover, the IT-landscape of InsurCo is vastly complex so that it would require extensive knowledge of the IT-landscape in order to be capable of implementing DS models.

The responsibility for data security and privacy is handled differently across the segments. In Life, data are widely distributed throughout the departments. Therefore, every data owner oversees that laws and rules are not violated for the respective database. Overall, the IT department enacts information security, i.e. making sure that data are encoded and that only authorized individuals have access. With respect to data privacy the IT-department, however, enforces a decentral data privacy governance, where every data owner and every person in charge of use cases is required to fulfill this governance. From our point of view, data scientists are not in charge of this topic as literature had initially suggested (Baškarada & Koronios, 2017) but are rather obliged to comply to these rules set by the lawmaker, the works council and the IT department.

In the previous paragraphs, we already identified the perceived and occupied roles and tasks of data scientists. With a brief look at the skill-set of the data scientists, we verify whether data scientists can actually carry out the discussed roles and tasks. Both role-senders and role-receivers agree that a data scientist requires statistical and programming knowledge. These skills are needed to apply DS methods (Davenport & Patil, 2012). The translation of complex ideas and results as well as all tasks within the business sphere require two important skills: business knowledge and soft skills, especially communication and presentation skills. There is a conflict in the role-senders' and role-receivers' impression of whether data scientists require these skills.

In accordance with the data scientists' belief that they generate insights and give recommendations, they are unanimously convinced that they require business knowledge. When asked about what type of skills they are looking for in the recruitment process, a DS manager argues: "The first topic is of functional nature. Does the applicant understand the business? Because in the end a data scientist that says 'give me the data. I want to calculate my model', will add zero value." (IP17, Manager Data Science, Market). Although these business skills are checked within the job interview, they are not a key requirement within the job advertisement for DS positions at the case company (InsurCo job advertisement). Management accountants' opinions do not match on this topic. Some argue that "a basic understanding would be nice, but we have Finance departments for economic KPIs, (…) because they require the know-how of a management accountant" (IP14, Manager Management Accounting, Health). Based on the perception through prior interactions with DS others reckon that "it is inevitable that data scientists have business knowledge" (IP7, Manager Management Accounting, Life). In the beginning it was noticed that the questions, which data scientists raised, were rather elementary, but that they were able to improve their know-how significantly over time.

Moreover, data scientists unanimously assess that they require the skills to communicate their findings, i.e. “to make the insights talk” (IP9, Data scientist, Market). This is in line with the job advertisements. Some key requirements of DS jobs are “strong communication skills” and the “ability to communicate complex analytical and technical content to a non-specialist audience” (InsurCo job advertisement).

> If I do not possess the capability to communicate adequately to the recipient, then I won’t generate much value for the company. (…) Especially this ability (…) is really central, much more important, much more crucial for the success of a data science project, then to know method A or method B. (IP8, Manager Data Science, Health)

Some role-senders, nevertheless, notice that certain data scientists do not have “black belts in communication” (IP5, Manager Management Accounting, Life). They regard communication skills as being “of advantage in case they have them” (IP15, Manager Management Accounting, Health), but not as a prerequisite. It is rather surprising that some role-senders expect data scientists to have neither business nor communication skills, although they require the translation of problems and, subsequently, the generation of insights from them. *Appendix C* summarizes the previously given empirical findings of RQ1.

4.2. Interactions between Data Scientists and Management Accountants

In this chapter, we strive to investigate the interactions between management accountants and data scientists, as motivated under RQ2, in more depth. By classifying the interrelations in accordance with Lado et al. (1997), a screenshot of the current power dynamics within InsurCo is given.

4.2.1. Task Monopolies of both Professions

Within the case company one target area of investigation is the interplay of data scientists and management accountants with respect to low value-add financial reporting activities. No evidence indicates that data scientists are active in this field. Thus, we observe a clear monopoly of management accountants with respect to financial reporting tasks. The reasons are twofold. On the one hand, it is argued that financial reporting tasks require specialist knowledge, but “the data scientist has no clue about this whole financial reporting topic” (IP14, Manager Management Accounting, Health). On the other hand, data scientists are perceived as too valuable resources for low value-add activities, such as reporting (Cokins, 2013). This exemplifies, furthermore, how traditional MA tasks are classified as dirty work (Hughes, 1951; Morales & Lambert, 2013) within the organization.

> Reporting - very limited, because if that's a question of where I say - I'm producing a recurring view on the same data - then hopefully it's a role where you will not need a data scientist anymore. (IP22, Manager IT)

While management accountants take on the responsibility for financial reporting tasks at InsurCo, data scientists arguably have a monopoly on BI&A systems and related models due to their technological know-how. Even an Operations manager with a mathematical education clearly states that instead of them the data scientists' role is to "build state-of-the-art models, (…) because I did not have a focus on such topics during my mathematical education" (IP21, Manager Operations, Health). In accordance with the previous role discussion, the BI&A system monopoly clearly links back to the role expectations role-senders have towards data scientists due to their statistical and programming know-how. The same Operations manager, however, also points out that data scientists' modeling skills are further used for legitimation reasons by top management when taking decisions. Since models are created by expert departments, i.e. DS, top management shows a high level of reliance and arguably uses these models as 'answer machines' (Burchell et al., 1980). We argue that the model and system monopoly of data scientists is encouraged by top management as it facilitates a clear responsibility and accountability. At the same time, the reliance on models for decision-making purposes clearly distinguishes data scientists' tasks from dirty work due to its direct impact on decision-making. However, we observe that this development is highly related to the track record of DS departments. In the interviews, it became clear that management loses trust to some degree in the newly established DS team since model results are incorrect at certain instances as a management accountant illustrated.

> Especially if they [top managers] question things, which are marked as correct, and then it turns out that these have been checked within the first review process, but the second review process is still missing, and no one has stated that. In these cases, trust is definitely lost. (IP7, Manager Management Accounting, Life)

Even though role-senders regard the process of insight generation as a black box (see *section 4.1.1.*), it seems that top management does not blindly follow the results of DS tools. This is because they are challenging the results of the DS departments and require a track record as a prerequisite for their trust. Quattrone's (2016, p. 120) fear that BI&A systems would "make people take wrong decisions much more quickly" is, therefore, rejected in the case company.

4.2.2. Syncretic Interaction through Transfer of Data Science Models

Syncretic behavior is characterized not only by high competition but also by high collaboration. Data scientists and management accountants compete for the generation of insights at InsurCo. In the previous section, we were able to illustrate that DS teams have established a monopoly related to the BI&A systems. However, this monopoly is undermined by the limited business know-how of the youngest DS department, as illustrated above. Top management tries to counterbalance these shortcomings through the establishment of working groups to support data scientists. We argue that this constitutes a syncretic environment since the involved parties are on their own insight generation experts but at the same time have to collaborate in order to enable data scientists. It is in these instances that especially management accountants take on a strong validation role due to their industry and task expertise and, thus, are able to ensure a higher quality through an iteration of the results with the DS team. These findings are in line with the role of an 'informed skeptic' that McKinney Jr et al. (2017) perceive as crucial. According to them, management accountants shall take on a critical stance to prevent the use of BI&A systems as answer machines (Burchell et al., 1980). While we observe a validation of DS results within the Life segment, management accountants' role of informed skeptics is of rather temporary nature. Based on the observations of more mature DS teams, we argue that those teams have accumulated enough business know-how and due to an established track record with top management, are less reliant on management accountants and Operations experts as sparring partners.

> It [the Health DS team] has profound knowledge of [the] Health [segment]. So, I can discuss individual service types with them – outpatient, stationary or with respect to dental care. (IP11, Manager Management Accounting, Health)

Based on their empirical findings, Morales & Lambert (2013) find that data validation constitutes dirty work for management accountants. In their setting, Operations professionals actively delegate the cross-checking of their computations to management accountants as they do not want to be engaged in these tasks themselves. As we find the degree of validation work to be related to the maturity of the DS department, it is assumed that errors are not created due to a lack of motivation but rather a lack of business know-how. Therefore, management accountants' data validation role does not constitute a form of dirty work at InsurCo but is a prerequisite for the data scientists' success in their interactions with top management. In contrast to the findings of Morales & Lambert (2013), management accountants, thus, engage at least to some extent in a business partner role themselves in our case setting.

Interestingly, data scientists express their desire to hand over the operation of their models to other organizational players, such as management accountants. This constitutes a highly collaborative attitude. Data scientists perceive the handling of the models and the mere execution of related business partnering tasks to be dirty work. Therefore, they try to distance themselves from these activities (Ashforth et al., 2007; Friedman & Lyne, 2001; Morales & Lambert, 2013) and strive for more prestigious endeavors, such as the ownership of the data strategy. At the same time, however, this collaborative attitude might lead to competitive implications, i.e. a data-driven as opposed to emotional decision-making, in the long-run. It can be argued that the control of the organization's digital mindset would elevate data scientists' reputation and role as data experts significantly. Data scientists already perceive that top management has a clear role expectation of them as crucial partners within data strategy issues.

> What is our data strategy? What is our Data Science strategy (…)? With respect to these topics, I was just yesterday in a five-hour meeting, in which we developed a recommendation for him [the responsible board member], which he can bring to the board meeting and present it to the CEO. (IP17, Manager Data Science, Market)

Moreover, it might be a strategic move to further establish their models within InsurCo by broadening the user base. This would also, in accordance with the technology power loop (Newman & Westrup, 2005), strengthen their organizational position. Accordingly, we find signs that data scientists advocate a data-driven decision-making regime that positions DS models as answer machines (Burchell et al., 1980), clearly favoring numbers over emotional and political aspects. By contrast, management accountants at InsurCo have a more contextual understanding of data, since they understand the decision-making process rather as a stage with emotional and political interests. This understanding of their role and the usage of data is in line with the findings of Goretzki et al. (2018), who outlined the ways management accountants use informational tactics to "deal with an often quite complex set of expectations and interests" (Goretzki et al., 2018, p. 721). Thus, we argue that a latent competition of ideologies is ongoing at InsurCo.

The different ideologies of the DS and MA departments come to light in the fields of cost allocation and customer cancellation. One management accountant within the Life segment states that he cannot see the DS team take on any tasks related to cost allocation. The task is described as highly emotional due to the impact on bonuses and, thus, would require a profound understanding of the organization to find acceptable results for all parties. In contrast to that, data scientists seem to be rather rational. The Market team is regularly involved in cancellation discussions for seemingly unprofitable customers. According to a data scientist, they would clearly pursue the best interest of the company by following the results of their DS models. This also means that they would not compromise because of political sentiments and strive for value maximization of InsurCo as a whole.

> We just got in there and then said, we do not only look at the contract but also whether the customer has something else. Maybe he also has a life insurance, another property contract or another health insurance [...] Although it is unprofitable for you [a single segment] at this time, the damage to [InsurCo] is greater if the customer would leave completely. (IP17, Manager Data Science, Market)

Consequently, management accountants seem to engage more in mediating positions, while DS teams try to give triggering impulses into the organization. These findings are in line with Goretzki & Messner (2018), who find that professions taking on a business partner role, act as challenging managers. In contrast to a setting where management accountants try to hide their loyalty through informational tactics (Goretzki et al., 2018), the phenomenon of challenging managers is observed when a clear loyalty towards a superior, in their case the CFO, is present. The same arguably applies to the data scientists at InsurCo. They have a clear loyalty towards the board of directors and are, therefore, less concerned with the consequences on their relationships with other stakeholders. They seem to be rather concerned with the creation of a digital mindset and the establishment of a symmetric information distribution throughout the organization, which at least to some degree is challenging the informational tactics management accountants use at InsurCo.

4.2.3. Competitive Attitudes Triggered by Top Management

Besides the previously described syncretic interactions, the generation of insights in the form of performance measurement or business partnering is mostly exposed to competitive behavior between management accountants and data scientists. Creating and tracking KPIs has traditionally been a core task of management accountants (e.g. Cokins, 2013; Simons, 1994). At InsurCo, this key competency gets, however, challenged by data scientists. While the interactions between the DS team and the management accountants within the Life segment seem to be syncretic, i.e. the management accountants supply their KPIs and support the DS teams to create own KPIs, the more mature DS departments do not interact anymore with the MA departments with respect to KPIs. Using the terminology of Lado et al. (1997), we interpret this relationship as competitive since the data scientists perform typical MA tasks by directly collaborating with the Operations departments, surpassing management accountants.

Besides active attempts of the DS team to take on MA tasks, such as the competition for the provision of KPIs, we find top management influences to be significant factors contributing to a competitive relationship between the DS and MA departments. Even management accountants recognize that data scientists are made an organizational priority, while they get to a certain degree deprioritized. The ‘high value’ perception of the DS team can be shown by the following quote, in which it becomes clear that top management excludes management accountants from discussions and directly communicates with the DS and Operations department.

> When the board directly intervenes, then they do not care about agreed-upon communication processes, but they talk to those important to them. This makes it in some instances difficult and brought us into a situation, where we did not know what was going on there [in the Operations and Data Science department]. (IP5, Manager Management Accounting, Life)

Thus, MA faces devaluating forces on their work. Not only the low value perception of reporting tasks and the presented communication pattern illustrate these forces. Moreover, the fact that the board has decided to give other professionals, in the form of newly hired data scientists, a leading role in creating a digital mindset and being in charge of the BI&A systems are examples of the neglection of MA. It seems to be a clear board decision to allocate resources for BI&A competences to DS departments and not to MA teams.

> The ‘customer churn prediction model’ is a topic that also the [Data Science] departments are dealing with. And because of time constraints, because we had to tackle many projects at [InsurCo], [system] migration, etc. (...), that is why our department, due to the limited amount of people, was not able to address these interesting, exciting topics. (…) I would claim, that if we would have received the time or the manpower, there would have been no need for a [Data Science] department. (IP14, Manager Management Accounting, Health)

The above quote clearly illustrates that management accountants in the Health segment at least punctually believe that they have the capabilities to take on DS models and see some of the tasks allocated to the DS team to be an interference with their area of competencies. Rather than engaging in DS tasks, management accountants perceive themselves to be tied up to a high degree with reporting and performance measurement tasks, which are regarded as low to modest value-add (Cokins, 2013) and preventing them from being engaged in business partnering tasks (e.g. Goretzki & Messner, 2018). Following the argumentation of Newman & Westrup (2005), the DS teams at InsurCo might, thus, be able to gain control over BI&A systems and accordingly redefine their expertise so that they position themselves as the most adequate professional group to be in charge of e.g. the customer churn prediction model. Additionally, in this instance, we perceive a high degree of role ambiguity between data scientists and management accountants. There is no clear communication from top management with respect to responsibilities, which consequently makes management accountants also claim the responsibility over the customer churn prediction model.

A further variable strengthening data scientists’ pole position within the BI&A sphere is its unique data access compared to other departments. This access enables them not only to access the ERP system or data marts from the BI layer but also to use the raw basis layer for their analyses. Compared to that, management accountants, to our understanding, have a rather modest access to different data sources. This would mean that, even if MA departments would be freed up from their current tasks to engage in DS analyses, their fundamental prerequisites, i.e. the data access, would still limit their chances of success compared to DS teams.

Throughout the interviews, it became clear that one of the greatest challenges DS teams face are related to the presentation of findings to decision-makers. The visualization of results seems to be not only a problem for the youngest DS department but still poses difficulties for the most senior data scientists within the case company. This creates tensions for the relationship between data scientists and the top management team. Contrary to this, management accountants are perceived as visualization experts with expertise in briefing a time-constrained top management.

> I often thought they [data scientists] should visualize it differently for this target audience [top management], since a management team that comes in and only has an hour wants to understand 'tack, tack, tack'. They [top managers] need to see the same graphics again and these should change. But if I start to bring new graphics and start explaining from the beginning, then I create resistance. (…) Even if it's pretty, (…) they [data scientists] did not accomplish what they wanted. Because top management is too far away from the topic, doesn't understand the number, doesn't understand the legend, doesn't understand the problem and actually doesn't want to understand it. They rather want to see, 'aha it changed from orange to green' and depending on that they must act or not. (IP7, Manager Management Accounting, Life)

Since management appreciates a clear and comprehensive presentation of results, these communication and visualization competencies might be significant reasons why management accountants are still perceived as crucial for the company's steering process. Management accountants' clear focus on reporting tasks and the related visualization focus can be interpreted as an indirect factor for the maintenance of management accountants' organizational status.

4.2.4. Collaborative Teamwork Resulting from low Role Ambiguity

Even though a high degree of syncretic and competitive interactions can be perceived between both focus parties, several collaborative relationships could be identified throughout the interviews.

As mentioned previously, the Market team collects and aggregates customer data from all company segments to enable a combined customer analysis. In this context, a database was created by this team. Management accountants make use of this data base for the annual report when it comes to mandatory customer-related figures. The collaboration on that level has, moreover, beneficial effects for both parties as their individual customer data are being validated through an iterative process, and management accountants get access to further customer insights. In most instances, however, the MA departments seem to be the stronger collaborative force by supplying data as well as data logic.

> Right now, management accountants are mainly the data source. The reason is that they are owners of a data mart with some figures that they need for getting the balance sheet and profit & loss. They need those numbers for regulatory purposes. But it turns out that these numbers are the most appropriate data source we have to analyze internal workflows. (…) That is why we basically collaborate with them. (IP1, Data scientist, Life)

> We have discussions with the colleagues [data scientists] when we supply data to them. What are these data? Where do they come from? Are these one-to-one relationships? Are those newly defined attributes? Why are they defined like this? From which sources do they originate? (IP14, Manager Management Accounting, Health)

With respect to process optimization and the customer lifetime value, and in contrast to the previously mentioned customer churn prediction model, there seems to be no competitive behavior but rather a collaboration between both parties. We potentially justify it with the fact that these tasks were added to the task spectrum of the organization and not redistributed.

> I would say we have expanded the whole spectrum of Management Accounting. Simply different insights are generated compared to standard reports. And we took on the task very much as a complement. (IP23, Manager Data Science, Health)

Another collaborative link between both focus professions can be found with respect to privacy and data security. As illustrated, management accountants provide data scientists regularly with their data. In the corporate context, however, due to e.g. agreements with the workers' council, analyses that might allow employee performance comparisons are prohibited. Especially in the youngest DS setting, management accountants and the IT department take on the leading role in ensuring compliance with regulatory standards. Management accountants do not perceive this task as pleasant but are rather obligated to do so due to their data ownership function, which inherently includes compliance work. At the same time, data scientists seem satisfied not to oversee data security and compliance tasks as they can fully focus on their tasks. This is why we interpret privacy and data security to constitute dirty work. It can be argued that the more decentralized data structure might have led to these findings within the Life segment. It should be stated that we do not find any similar observations with respect to the privacy and data security tasks for the other two DS departments.

Within the oldest DS department, we identify significant collaborations with management accountants during the annual general meetings. The collaboration between the most mature DS team and the MA department seems to have genuinely outgrown any competitive sentiment by displaying a feeling of 'teamwork'. In *section 4.2.3*, it was demonstrated that top management's communication style as well as the created role ambiguity, due to lacking direct task allocation, has a negative impact on the interaction between data scientists and management accountants. Contrary, in the case of the Market team, top management is able to create a strong team feeling by establishing data scientists and management accountants as equally important advisors at the annual general meetings. This feeling of collaboration is arguably then also extended to other tasks, such as planning, where data scientists support management accountants.

> During annual general meetings management accountants and we [data scientists] sit together – the back office so to say – to help the board to answer difficult questions. This is one type of interaction and then there is also planning. We do not count customers for fun. We also create a one- or three-year plan, and there is a planning process, that is run by the Management Accounting department. There we work closely together by jointly thinking on which basis we can plan the whole thing. Those are classic Management Accounting tasks, where we interact and have an established collaboration. (IP17, Manager Data Science, Market)

The creation or elimination of role ambiguities seems to be a key explanatory variable for competing or collaborative attitudes between data scientists and management accountants. Especially a clear communication of responsibilities and task requirements might reduce the claims of the excluded party. Furthermore, we could observe that the same data scientists, especially in the Market team, engage in different roles ranging from challenging managers to team workers. Consequently, data scientists also make use of political tactics (Goretzki et al., 2018) to strengthen their organizational status. This is surprising since they are advocating a data strategy with the maxim of transparency. However, it can be argued that they need to adapt to the organizational power dynamics by joining the political game in the meantime. *Appendix D* provides a concise overview of the empirics related to RQ2.

5. CONCLUDING DISCUSSION

Within this concluding discussion, we answer the RQs separately and close with a general outlook for the MA domain.

5.1. Data Scientists as a New Breed of Business Partner

Prior research shows that the role of the management accountant is at times ambiguous for other professionals (Byrne & Pierce, 2018) and that management accountants frequently have to cope with role conflicts due to different role expectations from other professions (Byrne & Pierce, 2018; Goretzki et al., 2018; Maas & Matejka, 2009). In our empirical setting, role-senders are mostly uninformed about the data scientists' tasks and workflows. Thus, we believe that data scientists' role ambiguity is at least equally if not even more pronounced than that of management accountants. The way how both professional groups handle these complications differs. While Goretzki et al. (2018) show that management accountants use informational tactics, data scientists at InsurCo manage role-senders' expectations in a highly transparent way and, thus, aim at reducing role ambiguity through proactive steps of role making. The proactivity of the data scientists, which is often assigned to management accountants by prior research, underlines a typical characteristic of a business partner (Goretzki et al., 2017). Since the role ambiguity is a major obstacle in the data scientists' daily work, they strive to create a digital mindset within InsurCo. This way data scientists act as change agents within InsurCo. A higher digital awareness may enable them to raise the quality of their analyses in the long-term and, in turn, further increase top management's reliance on data scientists as business partners. Consequently, with respect to the task dimensions, we add to existing literature that the data scientist's job – independent of the respective DS department's maturity – is to manage expectations of role-senders due to a high degree of role ambiguity and excessive expectations.

Nevertheless, we believe that data scientists also make use of the prevailing role ambiguity. Through the vague and abstract definition of business partnering tasks (Siegel & Sorensen, 1999; Sorensen, 2009) and the unclear distinction between them and management accountants it becomes unnoticed that boundaries towards MA are crossed (Ezzamel & Burns, 2005). Consequently, we argue that although they strive to increase transparency, they do not exclude themselves from political powerplays. In this empirical setting management accountants do not conduct 'boundary work' (Gieryn, 1983), i.e. they do not establish a clear 'demarcation' of their domain. Thus, data scientists have the possibility to take over MA tasks. We deem a clear role definition, beyond abstract business partner tasks of not only data scientists but also management accountants to be crucial for a reduction of the role ambiguity. However, if roles are clearly defined, this might trigger a role conflict nonetheless because tasks may be relocated away from the currently executing party.

Within the system sphere, we agree with previous research that data scientists employ DS tools and translate complex ideas and results (Davenport, 2006; Davenport & Patil, 2012; Kim et al., 2016). Within InsurCo, however, data scientists are neither in charge of the implementation of the developed BI&A systems nor primarily responsible for privacy and data security. These tasks are covered by the IT department and supported by management accountants. Thus, we disagree with prior practitioner-oriented research that data scientists are in charge of these tasks (Baškarada & Koronios, 2017; Henke et al., 2018; Kim et al., 2016; Power, 2016). This finding might, however, be related to contingency factors since IT systems within the insurance sector may be more complex than in other industries. We contribute to the literature that data scientists clearly enhance the digital infrastructure of organizations.

Within the business sphere we provide evidence that confirms prior research findings (Braganza et al., 2017; Carillo, 2017; Davenport, 2006; Davenport & Patil, 2012; Kim et al., 2016; Mohanty et al., 2013; Patil, 2011; Provost & Fawcett, 2013) by showing that the tasks executed by data scientists are within the MA domain (Cokins, 2013), i.e. performance management and business partnering tasks. Linking back to RQ1 we, thus, conclude that the data scientist's role indeed coincides with that of the management accountant. Data scientists can be seen as a new breed of business partners. Opposed to prior research (Ezzamel & Burns, 2005; Vaivio, 1999), our empirical setting illustrates that management accountants concede ground within the business partner function despite having more operational expertise than data scientists. Similarly, management accountants within InsurCo work decentralized, i.e. close to operations, which would facilitate to take over a business partner role according to empirical research (Granlund & Lukka, 1998; Järvenpää, 2007), but the organizationally rather distant DS teams manage to take over such tasks, nonetheless. Due to this overlap of roles a significant role conflict can be identified between management accountants and data scientists. Based on the framework of Katz & Kahn (1978) one would expect that decision-makers name one party as their business partner. However, as opposed to the theory of Katz & Kahn (1978), it might be the case that two similar roles may coexist. This could be the case if the implied advantages of a continuous role overlap prevail over the related disadvantages, such as role conflicts. An example for such a successful coexistence is given in *section 4.2.4.* illustrated by the teamwork at the annual general meeting, which emerged through a concise up-front top management communication. *Appendix E* summarizes the comparison between the tasks assigned to data scientists by literature and those observed within the empirics.

We conclude that data scientists do not act in isolation within the IIS domain. This professional group unleashes from its native domain and pushes towards the MA domain by taking the proactive role of an enabler and a translator of business problems into analytical problems. Thus, the data scientist acts as a hybrid profession between IIS and MA. These professionals take over MA tasks (Cokins, 2013), and, therefore, occupy to some extent the management accountant's nest, inversely to what Caglio (2003) identifies within the ERP era (Jack & Kholeif, 2008). Nevertheless, the work conducted by the data scientist is not a one-way street towards the MA domain. By taking on the role of a change agent not only management accountants but also the entire organization is pulled towards the IIS domain. In conclusion, the data scientist's actions implicate that the MA and IIS domains, which are identified by Rom & Rohde (2007) as interrelated but still separated worlds, further approach each other.

In the subsequent section, we investigate whether data scientists enter the management accountants' nest to stay and to take on their role or whether the data scientists' intentions are to guard the management accountants' nest and to cooperate side by side.

5.2. Versatile Interactions Highly Influenced by Top Management

Even though management accountants historically were often able to strengthen their organizational position and extend their task spectrum by system ownership (Caglio, 2003; Newman & Westrup, 2005; Whittington & Whipp, 1992) and informational tactics (Goretzki et al., 2018), they nowadays face a strong rivalry from other professional groups. As we could illustrate in our analysis, the means management accountants used in the past to enforce their organizational status, are strongly curtailed by the rise of the DS profession. To our surprise, however, the interactions between data scientists and management accountants show a broad range of patterns and demonstrate that the answer to RQ2 is versatile.

Literature regularly ascribes system ownership as one of the means applied by management accountants to gain organizational power (Newman & Westrup, 2005; Whittington & Whipp, 1992). In the case setting, management accountants were and still are the leading professionals with respect to the ERP system. However, data scientists at InsurCo were able to create a BI&A system monopoly and unique data access. They have, consequently, been able to create a technological superiority over management accountants. Analyzing the role expectations of other organizational parties towards the data scientists, this technological superiority is confirmed. According to Whittington & Whipp (1992), professions are able to improve their organizational standing by establishing a 'professional apparatus' and 'sophisticated mathematical models'. Overall, we agree with prior research (Newman & Westrup, 2005; Whittington & Whipp, 1992) that the monopoly of the sophisticated models can be regarded as a key reason for data scientists' organizational success at InsurCo. In line with this, especially the interactions between the second oldest DS department, Health, and management accountants can be classified as competitive and challenging the management accountant's organizational status. In the empirical setting, it is not the management accountant but rather the data scientist who makes use of exclusion tactics (Whittington & Whipp, 1992). This, in turn, enables the Health DS team to take on e.g. the customer churn prediction model, that is also targeted by the management accountants.

Not only system ownership but also the political skills (Armstrong, 1985; Richardson, 1988; Whittington & Whipp, 1992; Willmott, 1986) and respective informational tactics (Goretzki et al., 2018) are perceived by previous research as important instruments of traditional management accountants to establish themselves within organizations. Within the case setting, it is observable that data scientists actively reshape the digital mindset and strategy of InsurCo, with the ultimate goal to enhance transparency and symmetric data provision throughout the whole organization. This transparency, in turn, significantly reduces management accountants' ability to engage in informational tactics and, thus, severely cuts their political influence. Even though the competition over data ideology between data scientists and management accountants is rather latent at the time of investigation, DS departments successfully position their systems and models as answer machines (Burchell et al., 1980) for top management decisions. As we show, systems as well as system owners have to overcome a legitimization phase first, before answer machines are actively used by top management. During this process MA departments take on a validation and a sparring partner role. Therefore, the youngest DS department has highly syncretic interactions with the MA team. Consequently, management accountants are following the call of McKinney Jr et al. (2017) to become informed skeptics, who counterbalance the intended use of DS tools as answer machines (Burchell et al., 1980; Quattrone, 2016). In contrast to Quattrone's predictions, that management accountants would benefit from this engagement, data scientists are able to rely less on management accountants' validation role over time, because they accumulate significant business know-how themselves. Interviewees confirm, that top management has a high degree of trust in the results of older DS departments once a track record is established. We, therefore, reject Quattrone's (2016, p. 121) claim that MA "will keep flourishing as it has for hundreds of years" by taking on an interrogation role.

Even though all interviewees at InsurCo consistently state that DS teams need to deliver tangible results, there are currently, to the best of our knowledge, no controls in place to measure data scientists' performance. Similarly to Ezzamel & Burns (2005), it is difficult for management accountants to impose controls over the DS departments since especially top management advocates a relatively loose steering of DS teams in order to facilitate their creativity. This is further complicated by the fact that data scientists proactively shape their role to retain their flexibilities.

In line with that, we find top management support to be a relevant force for the data scientist's success. This link has already been established by prior research, however, with management accountants as focus professionals (Järvenpää, 2007, 2009; Wolf et al., 2015). DS is actively articulated as a top management priority, which is also indirectly reinforced by the organizational positioning directly below the board of directors. While data scientists are actively promoted and shaping their organizational reputation through active role making, management accountants and their task monopolies are in several instances devaluated as dirty work. In line with this, organizational players describe the engagement of data scientists in e.g. financial reporting tasks, a traditional MA field, as a waste of resources. Moreover, it can be perceived that data scientists see themselves as 'information worker elite', who aspire to delegate the pure operational execution of their models to other professions, such as management accountants. This would enable the DS teams to be free from repetitive, operational tasks and to engage more in the creation of a digital mindset as well as more explorative tasks, which are perceived as strategically more important.

Following our empirical findings, it is surprising to observe largely collaborative interactions between both focus professions. Not only MA departments are to a high degree sharing their data and data logic with the DS teams at InsurCo but also especially the oldest DS department, Market, has in contrast to the other DS departments a highly collaborative relationship with MA teams. The supply of customer data and the illustrated 'team spirit' among 'the back office' are exemplary of this. In this context, we find a transparent top management communication as well as a clear task allocation to be of high explanatory power. A further explanation for the collaborative behavior of the Market department can be found in the relatively high degree of recurring tasks and interactions with management accountants. We infer that this encourages both parties to be at good terms with each other. In contrast to that, the rather competitive behavior in the Health segment is at least partially attributable to a lack of the previously mentioned factors.

At the same time, however, all DS departments can be characterized as challenging the business (Goretzki & Messner, 2018) at times, in order to ensure rational value maximization over political or emotional decision-making. In line with Goretzki & Messner (2018), we argue that this can be attributed to data scientists' loyalty towards the board of directors. This is, on the one hand, reinforced by the direct reporting to one of the board members and, on the other hand, by the loose responsibility towards other organizational players due to their rotating project focus. We, consequently, infer that data scientists, following the different attitudes they illustrate, also engage in informational tactics (Goretzki et al., 2018) despite their neutral appearance.

Management accountants historically made use of role ambiguities by adjusting their profile according to the organizational recipient (e.g. Goretzki et al., 2018). In contrast to that, our analysis shows that the elimination of role ambiguities, initiated by data scientists, results in task losses for the management accountants. The pursued transparency and role making of data scientists are seen as tools to take possession of tasks that previously were not officially allocated to but occupied by different professional groups, such as management accountants. These observations, however, are not only restricted to the interactions between data scientists and management accountants. Other departments, such as Actuary departments, also perceive their task-set to be challenged by data scientists, who are free from operational duties to a much higher extent than established departments. Especially the influence of top management can be seen as one of the central variables impacting the interactions between data scientists and other professional groups within InsurCo. Overall, these findings on the interactions between data scientists and management accountants are novel contributions to literature and are an invitation for further research.

5.3. Outlook for Management Accounting

This empirical case study shows that management accountants fail at establishing themselves as business partners and are rather pushed towards a bean-counter role instead. We analyze the professional interactions between management accountants and the emerging data scientists. Factors that according to prior research enable management accountants to take on a business partner role do not apply in the same way to our empirical case. Management accountants lose their organizational status because of several contextual reasons. While management accountants have neither the time nor the manpower for executing additional value-generating tasks, data scientists benefit from their high flexibility due to their project-based engagements. Furthermore, top management substantially supports DS departments in gaining organizational relevance and partially excludes management accountants actively from information exchange within DS projects. This exclusion of management accountants and the high degree of role ambiguity of both data scientists and the business partner role enable data scientists to claim high value-add business partnering tasks via role making.

Quattrone (2016) argues that the ‘digital revolution’ threatens the decision-making quality. However, we disagree with his idea since top management does not blindly use BI&A systems as answer machines in the case setting (e.g. Arnaboldi et al., 2017). He further argues that management accountants will be able to secure their organizational importance by challenging the results of new systems. Contrary to this claim, we identify that management accountants are pushed out of this validation role over time as data scientists earn a high degree of top management trust after they have established a track record. At the same time, data scientists succeed in burying other tasks, such as the IT implementation, the data privacy and security governance, and financial reporting tasks, which they consider to be dirty work (Hughes, 1951). Data scientists even strive to retreat from the operational handling of their models in order to break free from operational duties. This is not a new line of argumentation. Abbott (1988) illustrates that e.g. statisticians actively spread their techniques and refuse to take on an operating role in order to be engaged in more abstract activities. However, the fact that data scientists are hybrid professionals (Zschech et al., 2018), unlike statisticians, makes their appearance more challenging for management accountants. Additionally, most of the management accountants state that they currently do not possess the required skill-set to take over BI&A systems from data scientists. This is in line with the findings of Pincus et al. (2017), who find that management accountants' curriculum and skills have only insignificantly changed since the 1980s. While this not only poses a problem with respect to the lost dominance within the technology power loop (Newman & Westrup, 2005), it also opens up possibilities for other professional groups to gain status in the BI&A era (Arnaboldi et al., 2017). Following Arnaboldi et al. (2017), we contribute to this discussion by showcasing that data scientists are in charge of the most value-adding MA tasks, i.e. business partnering (Cokins, 2013), and are able to leverage their technological supremacy. The hybridization of management accountants enabled them to gain organizational recognition in the ERP era in many cases (e.g. Caglio, 2003; Goretzki et al., 2013). The BI&A era, in contrast, does not seem to be clearly in favor of management accountants and rather strengthens the decoupling of management accountants and MA tasks (Rom & Rohde, 2007). Overall, we find that the IIS domain, in the form of data scientists and BI&A models, actively shapes the tasks which management accountants perform. With respect to the management accountant's nest, it will be for the future to show, who will rule the roost.

6. LIMITATIONS AND FURTHER RESEARCH

The conducted study has a few limitations. Therefore, we raise suggestions for further research in order to not only point out how research can account for limitations but also demonstrate interesting topics deriving from this paper that require further examination.

Although we observed a broad role-set to analyze the role of data scientists, we acknowledge that the indications of management accountants might be politically biased due to the apparent competition for tasks. Moreover, the expectations of decision-makers could be observed to a limited extent only. Therefore, future research on the contested business partner ecosystem should continue to cover a broad range of independent role-senders, especially focusing on top management. This would allow a relatively unbiased assessment of roles. Additionally, it could be investigated whether top management communicates role expectations clearly and distinguishably. The decision-making process of how top management uses and challenges each profession's deliverables would be highly interesting to analyze with respect to the answer machine discussion (Burchell et al., 1980).

Contingency factors of this study, e.g. the highly-regulated insurance sector and national specifics in the corporate practice of MA (Ahrens & Chapman, 2000), may challenge the external validity for other industries as well as countries. Thus, it requires further research to assess whether our empirical findings are case-dependent or whether they are general phenomena, which can be similarly found in other organizations. A multiple case-study comparing the phenomena across industries or countries may be interesting in this light.

The highly ambiguous definition of both the business partner role and its composition (Mahlendorf, 2014; Siegel & Sorensen, 1999; Sorensen, 2009) complicated the concise allocation of roles to professionals and the distinction between them. We support Mahlendorf's (2014) request that research should establish a standard definition of the business partner role and a more detailed understanding of what it entails in order to better assess the degree by which individuals embody this role and to make research comparable.

As opposed to prior jurisdictional conflicts (e.g. Armstrong, 1985; Arnaboldi et al., 2017; Ezzamel & Burns, 2005; Whittington & Whipp, 1992), management accountants now face a new breed of business partner. Data scientists are less time-constrained through repetitive, operational responsibilities. Although this resembles to some extent the empirical setting of Abbott (1988), data scientists differ from the analyzed statisticians, because they seem to be truly hybrid professionals. Quattrone (2016) suggests that management accountants retain their organizational status by taking on an interrogating role. Since this did not hold in our empirical setting, further MA research may investigate what potential strategies management accountants apply to stay competitive.

7. APPENDIX

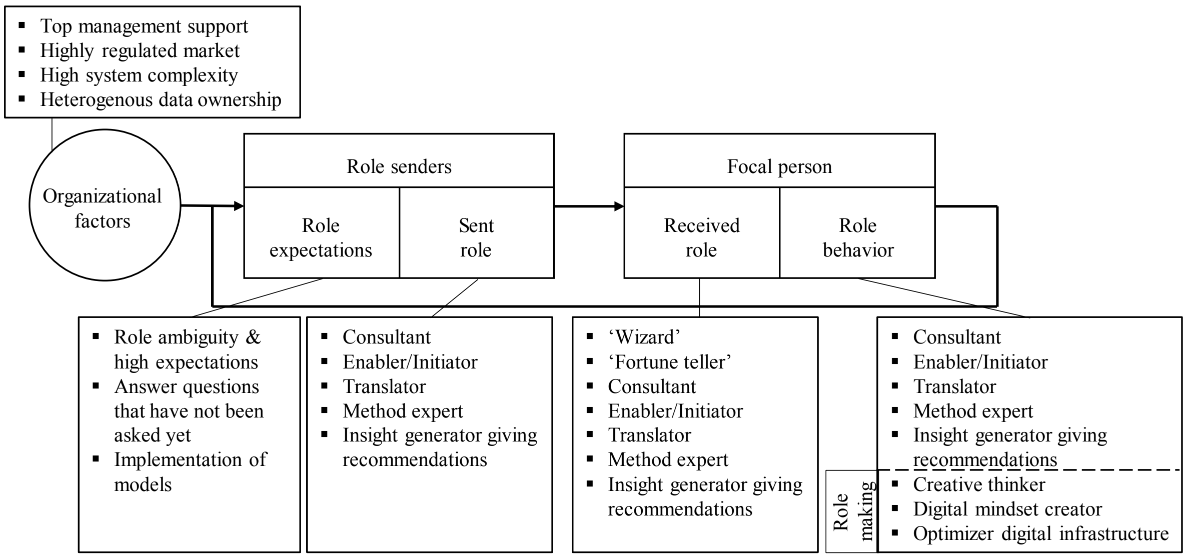
7.1. Appendix A. Overview of Conducted Interviews

#	Code	Interviewee	Segment	Location	Date	Length
1	IP1	Data scientist	Life	Location 1	18.02.2019	01:01:43
2	IP2	Data scientist	Life	Location 1	18.02.2019	01:01:43
3	IP3	Manager Operations	Life	Location 1	18.02.2019	00:50:04
4	IP4	Manager Management Accounting	Life	Location 1	19.02.2019	00:42:37
5	IP5	Manager Management Accounting	Life	Location 1	19.02.2019	01:16:05
6	IP6	Management accountant	Life	Location 1	19.02.2019	00:49:39
7	IP7	Manager Management Accounting	Life	Location 1	20.02.2019	00:50:22
8	IP8	Manager Data Science	Health	Location 2	04.03.2019	00:43:10
9	IP9	Data scientist	Market	Location 2	11.03.2019	00:50:47
10	IP10	Data scientist	Health	Location 2	11.03.2019	00:38:59
11	IP11	Manager Management Accounting	Health	Location 2	11.03.2019	00:27:55
12	IP12	Data scientist	Market	Location 2	11.03.2019	00:58:17
13	IP13	Manager Actuary	Health	Location 2	11.03.2019	00:34:59
14	IP14	Manager Management Accounting	Health	Location 2	12.03.2019	00:45:26
15	IP15	Manager Management Accounting	Health	Location 2	12.03.2019	00:45:26
16	IP16	Management accountant	Health	Location 2	12.03.2019	00:45:26
17	IP17	Manager Data Science	Market	Location 2	13.03.2019	00:53:12
18	IP18	Manager Management Accounting	Health	Location 2	13.03.2019	00:56:11
19	IP19	Manager Operations	General	Location 2	13.03.2019	00:51:39
20	IP20	Actuary	Health	Location 2	14.03.2019	00:42:40
21	IP21	Manager Operations	Health	Location 2	14.03.2019	00:32:14
22	IP22	Manager IT	General	Location 2	14.03.2019	00:46:14
23	IP23	Manager Data Science	Health	Location 2	14.03.2019	00:18:47

7.2. Appendix B. Excerpt of Question Catalog

Part	Questions
1. Introduction	▪ Please tell us about your role and tasks within the organization. ▪ What are your roles and tasks in the interaction with data scientists / management accountants?
2. RQ1	▪ What are the data scientist's tasks and roles in the organization? ▪ To what extent is it the data scientist's role to provide decision-making support, business partnering and monitoring KPIs? ▪ What skills do data scientists require? ▪ How do you assess success / failure in a Data Science project?
3. RQ2	▪ On which topics do you interact with the Management Accounting / Data Science team? ▪ Is it a good cooperation or do you clash sometimes? ▪ Have they taken over tasks from you? ▪ Have you taken over some of their models? ▪ What do you think will the interaction be in the long-run?

7.3. Appendix C. Data Scientists' Role According to Katz & Kahn (1978)



7.4. Appendix D. Interactions According to Lado et al. (1997)

Cooperative Orientation	Low (Competitive Orientation)	High (Competitive Orientation)
High	<u>Collaborative Behavior</u> ▪ Customer count ▪ Data security and compliance ▪ Annual general meeting ▪ Planning process ▪ *Variables: Top management communication, clear role definition*	<u>Syncretic Behavior</u> ▪ Result validation & insight generation (initial stage) ▪ Distribution of DS models & competing data ideology ▪ *Variables: Top management initiatives (working group)*
Low	<u>Monopolistic Behavior</u> ▪ BI&A systems (DS) ▪ Cost accounting (MA) ▪ *Variables: Specialist know-how*	<u>Competitive Behavior</u> ▪ Insight generation and presentation (later stage) ▪ *Variables: Top management communication, role ambiguity, data access*

7.5. Appendix E. Task Comparison between Literature and Empirics

Task dimensions	Management accountants	Data scientists	Literature examples
System sphere (examples)	Implementation of systems [1]	✗ Implementation of systems [2,3]	[1] Dai et al., 2013 quoted from Schneider et al., 2015 [2] Henke et al., 2018 [3] Power, 2016 [4] ISACA, 2014 quoted from Schneider et al., 2015 [5] Kim et al., 2016 [6] Davenport & Patil, 2012 [7] Brands & Holtzblatt, 2015 [8] Baškarada & Koronios, 2017 [9] Goretzki et al., 2013 [10] Becker & Heinzelmann, 2017 [11] Granville, 2014 [12] Cokins, 2013 [13] Appelbaum et al., 2017 [14] Patil, 2011 [15] Quattrone, 2016 [16] McKinney Jr et al., 2017 [17] Davenport, 2006 [18] Provost & Fawcett, 2013 [19] Carillo, 2017 [20] Braganza et al., 2017 [21] Mohanty et al., 2013
	Use of analytics tools [4]	✓ Use of analytics tools [5,6]	
	Privacy and data security [7]	✗ Privacy and data security [8]	
	Information gatekeeper [9,10]	✓ Data management [11] ▪ *Contribution: Expansion of digital infrastructure*	
Business sphere (examples)	Cost accounting / Financial reporting [12,19]		
	Performance measurement [12,13] ▪ Spending vs. budget variance analysis ▪ Profitability reporting	✓ Performance measurement [14]	
	Business Partnering [12,15,16] ▪ Process improvement ▪ Customer lifetime value ▪ What-if-analysis ▪ Rolling financial forecasts ▪ Critics, informed skeptics	✓ Business Partnering/Decision-making support [2,4,6,17,18,19,20,21] ▪ Process improvement ▪ Recommendation ▪ Insight generation and translation ▪ Visualization ▪ *Contribution: Expectation management* ▪ *Contribution: Promotion of digital mindset* ✓ Experimentation and exploration of possibilities [6]	

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