THE MANAGEMENT ACCOUNTING DEPARTMENT'S DATA SCIENTISTS

THE INTERMEDIARY IN THE BUSINESS ANALYTICS NETWORK

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The Management Accounting Department's Data Scientists: The Intermediary in the Business Analytics Network

Abstract:

Business analytics involves tooling, statistics, and mathematics for decision-making and reporting in the data-driven business era. It is an interdisciplinary phenomenon in which management accountants work together with data professionals. Management accountants must engage with business analytics to maintain their legitimacy in the data-driven business era. Therefore, this thesis aims to study how management accountants engage with business analytics and what role data professionals play in this process. A single case study was carried out at TechCo, a Swedish software technology company. The analysis found that management accountants engage with business analytics through a network of different actors. The thesis's main contribution to the interdisciplinary business analytics domain highlights the critical role that data scientists can play in bridging weak links in the business analytics network between management accountants, data engineers, and a data warehouse. The results have practical implications for creating data science teams to support management accountants with business analytics.

Keywords:

Business Analytics, Management Accounting, Data Scientist, Jurisdictions, Data Warehouse, ERP

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1. Introduction

Business analytics involves tooling, statistics, and mathematics for decision-making and reporting in the data-driven business era (Carillo, 2016; Davenport, 2014). Management accounting literature argues that business analytics is a cross-occupational phenomenon in which management accountants will work together with data professionals (Moll & Yigitbasioglu, 2019; Richins et al., 2017; Al-Htaybat & von Alberti-Alhtaybat, 2017; Barbour et al., 2018). However, there are conflicting views on how management accountants should engage with business analytics and what role data professionals will play in this process. This thesis aims to identify the mechanisms for how management accountants and data professionals collaborate and divide work in cross-occupational business analytics processes. This chapter will introduce the research by discussing the background, context, research problem, research aims, objectives and question, significance, and limitations.

Business analytics is nothing new; it is a term for working with and analyzing data, understood as the evolution of business intelligence in the data-driven business era (Carillo, 2016). The research area has seen an upswing of interest due to the big data and machine learning hype, two concepts that are often (quite confusingly) bundled with business analytics (Davenport, 2014). However, by focusing too much on big data and machine learning, you miss the forest for the trees (Carillo, 2016). The main problem in this management accounting sub-domain is that the profession is being pressured into becoming more analytics-oriented (Cokins, 2013). However, management accountants lack business analytics skills (Oesterreich & Teuteberg, 2019), and some research shows that management accountants actively resist moving away from Excel (Schmidt et al., 2020). This potential existential crisis resulted in articles that refuted that the accounting and management accounting professions were threatened by automation or more technical actors (see Richins et al., 2017; Moll & Yigitbasioglu, 2019; Al-Htaybat & von Alberti-Alhtaybat, 2017).

To remedy the problem, these articles propose various roles for accountants and management accountants in the business analytics domain. For example, as system evaluators (Moll & Yigitbasioglu, 2019), analysts of structured data (Richins et al., 2017), or collaborators with data scientists (Al-Htaybat & von Alberti-Alhtaybat, 2017). They also propose various types of relationships with data professionals. Either based on a transactional (Moll & Yigitbasioglu, 2019), divided (Richins et al., 2017), or collaborative (Al-Htaybat & von Alberti-Alhtaybat, 2017) division of labor. Thus, there are conflicting views on what management accounting should look like in the future. Furthermore, the literature does not describe the low-level mechanisms and conditions that would allow management accountants and data scientists to co-exist in an organizational context and jurisdiction that management accountants have historically dominated. As a result, the existing research is not helpful for practitioners who want to add data science resources to their management accounting functions due to increasing pressures to become data-driven (Carillo, 2016).

This study aims to identify and evaluate the mechanisms and conditions that allow management accountants and data professionals to co-exist and collaborate on business analytics at the Swedish software technology company TechCo. To support the analysis, I will lean on Anteby et al.'s (2016) *lenses on occupations and professions in organizations* framework, which provides a *doing lens* perspective to highlight jurisdictional tensions and a *relating lens* perspective to highlight mechanisms that allow for overcoming tensions. The following were my research objectives (RO). **RO1:** To identify the roles that management accountants and data professionals play in the business analytics domain at TechCo. **RO2:** To determine the mechanisms and conditions by which management accountants and data professionals overcome jurisdictional barriers to collaborate in the business analytics domain at TechCo. **RQ**: How do management accountants engage with business analytics, and what role do data professionals play in this process?

This study will contribute to the growing body of knowledge on cross-occupational work between management accountants and data professionals within the business analytics domain. This will help establish how management accounting can maintain its legitimacy in the data-driven business era where management accountants are pressured to become more analytics-oriented but lack the skills to perform business analytics efficiently and independently.

I acknowledge certain limitations with the study. One factor is the scope; the single case study format makes it more challenging to identify all moderating variables. A second factor is the time limitation, which led me only to perform twelve interviews, but direct observations partly alleviated this problem. Third, some moderating factors could limit the generalizability of my findings. For example, the fact that the study took place within the software technology industry, where data professionals are more established. Or within the pandemic work-from-home situation where social interactions have been limited to on-camera.

Chapter one discussed the research background, context, and problem. The research objectives and questions were presented. And the significance and limitations highlighted. Chapter two will review the existing domain theory to identify key perspectives on cross-occupational business analytics work and the increased analytics orientation of management accounting. Then, Anteby et al.'s (2016) framework will be presented as the method theory. Finally, the theoretical framework will be constructed. Chapter three presents the methodology of the study. Chapter four analyzes the empirical data using the Anteby et al. (2016) framework. Chapter five discusses the contributions in relation to the domain theory and presents the limitations, practical applications, and future research. Finally, chapter six covers the main findings, limitations, and areas for future research.

2. Theory

This chapter first covers the domain theory related to business analytics in management accounting, followed by the research question, method theory, and theoretical framework.

2.1. Domain Theory

The domain theory subchapter first discusses the problematic terminology within the business analytics domain. Second, it develops the idea behind an increased analytics orientation of management accounting. Third, it covers what I identified as the seminal works of the interdisciplinary business analytics domain. Finally, the subchapter concludes with a discussion of gaps in the literature and the presentation of the research question.

2.1.1. Business Analytics

The management accounting profession is either facing a significant shift in data use and analysis technologies, or such sentiments are being exaggerated by the big data and machine learning hype (Quattrone, 2016; Richins et al., 2017; Cokins, 2013; Appelbaum et al., 2017; Arnaboldi et al., 2017). Regardless, there is a significant spread in the terminology used to describe similar data-related domains. Some of the most pervasive terminology in recent years include "business intelligence," "analytics," "big data," "big data analytics," and "business analytics" (Carillo, 2016). Davenport (2014) argues that most of these terms are related to each other. And that they all involve the broader notion of working with and describing data but that each variation has a specific emphasis; see table 1. For example, "business intelligence" has a focus on tooling, "analytics" on statistics and mathematics, and "big data" on data characteristics.

Table 1. Evolution of terminology for using and analyzing data (Davenport, 2014).

Term	Time frame	Specific meaning
Decision support	1970-1985	Use of data analysis to support decision making
Executive support	1980-1990	Focus on data analysis for decisions by senior executives
Online analytical processing (OLAP)	1990-2000	Software for analyzing multidimensional data tables
Business Intelligence	1989-2005	Tools to support data-driven decisions, with emphasis on reporting
Analytics	2005-2010	Focus on statistical and mathematical analysis for decisions
Big data	2010-present	Focus on very large, unstructured, fast-moving data

However, the terminology is not clear-cut; researchers have had difficulties defining and delimiting the domain of big data and its related concepts (Carillo, 2016). This ambiguity has resulted in a fragmented research landscape, often set off course by media trends:

> For the sake of transparency and clarity, academia and the industry must join forces to standardize the meaning and scope of the terms surrounding 'big data.' […] The big data phenomenon is not a matter of size. It is about the central and critical role that data now plays in businesses and in our entire society. […] As a matter of fact, the term "[big data analytics]" is also evasive, "[business analytics]," understood as the evolution of [business intelligence] in the data-driven business era, seems more appropriate […] Overall, both the academia and business spheres must retake control on the significance of terms and notions as the big data debate has overly drifted away, pushed by the waves engendered by the constant attention the media have paid to the big data buzz over the last few years. (Carillo, 2016, p. 613)

In unison with the recommendations from Carillo (2016), this thesis focuses on business analytics as its primary data-related domain. This circumvents the complications inherent to the big data discourse. The business analytics domain is understood as "the evolution of [business intelligence] in the data-driven business era" (Carillo, 2016). Referring to Davenport's (2014) etymology from table 1, the specific meanings of "business intelligence" and "analytics" would suggest that business analytics as a domain includes tooling, statistics, and mathematics for decision-making and reporting within the context of the data-driven business era. However, as table 1 suggests, there is nothing inherently new with the business analytics concept; it is more of a generational upgrade from business intelligence. Still, it is a handy way to define the data-related domain because most data-centered management accounting literature can fit underneath the business analytics umbrella.

2.1.2. The Increased Analytics Orientation of Management Accounting

As was mentioned in the introduction, there has been an upswing in the interest in management accounting business analytics literature. This is related to the big data and machine learning "revolution" or "hype" (depending on how you see it) (Arnaboldi et al., 2017, p. 762). As a result of this hype or revolution, current business analytics authors tend to overcomplicate things. They often mix big data, machine learning, and business analytics into one confusing bundle. See, for example, Richins et al. (2017), where the authors somehow argue that accountants are well-positioned to perform machine learning using unstructured data. With such examples, one must take the current literature with a pinch of salt whenever big data is mentioned. As Carillo (2016) argued, big data tends to cause authors to get distracted by the discourse.

However, articles such as Richins et al. (2017) paint another picture if you read between the lines. The hype or revolution in big data and machine learning, or what Carillo (2016, p. 598) calls "the data-driven business era," puts pressure on management accountants to become more analytics-oriented. However, this is not a recent phenomenon. Cokins (2013, p. 26) highlighted back in 2013 that: "A gap is widening between what management accountants report and what managers and employee teams want," expressing that managers want forward-looking, high-value add inputs related to business analytics and big data. But, is it not worrying that the business analytics literature, more than half a decade later, still discusses management accountants' lack of analytical skills (Oesterreich & Teuteberg, 2019)? And even worse, some argue that management accountants actively resist learning other skills than Excel (Schmidt et al., 2020). But perhaps this means that the big data revolution was actually just hype?

I think not. In recent years, we have seen more articles talking about data scientists. The elusive profession was hypothesized to do it all: "Think of him or her as a hybrid of data hacker, analyst, communicator, and trusted adviser. The combination is extremely powerful—and rare" (Davenport & Patil, 2012, p. 73). However, even though some of that do-it-all mysteriousness has since gone away (Baškarada & Koronios, 2017), the data scientists have the skillset (Avnoon, 2021) to provide what the managers asked for back in 2013 (Cokins, 2013, p. 26). I believe that data scientists are the organizations' answer to what was effectively intentional self-undermining by management accountants when they did not adapt to the business needs post-2013. And, if management accountants were falling behind in technical analytics skills in 2013, do we dare to ask how far behind they are in 2022?

As a response to this potential existential crisis, a series of business analytics articles were published between 2017-2019, which essentially had to refute that the accounting and management accounting professions were threatened by automation and more technical actors (see Richins et al., 2017; Moll & Yigitbasioglu, 2019; Al-Htaybat & von Alberti-Alhtaybat, 2017). Again, the authors generally go deeper into big data, machine learning, blockchain, sentiment analysis, etc., than I believe warranted from a realistic accounting skillset point of view (Oesterreich & Teuteberg, 2019; Schmidt et al., 2020). However, if you read between the lines, these studies essentially say: Yes. The accounting and management accounting jurisdictions are under increasing pressure from technology experts.

Now, it’s been a couple of years since these articles came out, so the next generation of cross-occupational business analytics literature is likely on its way; unfortunately, I did not have access to any working papers. But I believe these articles (i.e., Richins et al., 2017; Moll & Yigitbasioglu, 2019; Al-Htaybat & von Alberti-Alhtaybat, 2017) are the seminal literature on management accounting’s collaboration with data scientists in the business analytics domain. I will also include Barbour et al. (2018) in this list; though not strictly related to accounting, its domain is very close. I will cover these articles in more detail in the following subchapter.

2.1.3. Interdisciplinary Business Analytics

This subchapter will try to clarify each article’s stance on interdisciplinary business analytics. It will also describe which roles they propose for management accountants in the business analytics domain and which types of relationships they propose with data professionals.

Moll & Yigitbasioglu, 2019

Moll and Yigitbasioglu’s (2019) literature review suggests that accountants are well-positioned to contribute to the evaluation, implementation, and maintenance of big data and machine learning technologies and processes. However, the authors cautioned that it’s still unclear if accountants can use their influence in these decisions to better compete in the business analytics space. Instead, they warned that accountants’ jurisdictions might “increasingly be challenged by other professions such as data scientists and technology experts” (Moll & Yigitbasioglu, 2019, p. 16). Thus, they believed accountants must adapt to and incorporate business analytics into their skill sets, recognizing that this has become increasingly important. I would describe Moll and Yigitbasioglu's description of the management accountant's role in business analytics as an evaluator in a mostly disjoint and transactional relationship with data professionals.

Richins et al., 2017

Richins et al. (2017) presented a conundrum; the recent abundance of information seemingly hasn't resulted in better decisions. The authors added that business analytics could either be the solution or worsen the problem. New technology can allow for more valuable insights, but insights are only helpful if the data is good and can be translated into business language. Data scientists have the skills to effectively work with complex data but may lack the domain knowledge to connect insights with business strategy. On the other hand, accountants may struggle with unstructured data but better understand how financial data can be translated into strategy. Reasoning along those lines, Richins et al. suggested that business analytics can be roughly divided into two categories, led by accountants and data scientists respectively; see figure 1.

		Data	
		Structured	Unstructured
Analysis approach	Theory-driven	accountant *(pre-big data)*	accountant *(post-big data)*
	Data-driven	data scientist *(post-big data)*	data scientist *(post-big data)*

Figure 1. Data analysis actors in a "pre-and post-big data world" (Adapted from Richins et al., 2017, pp. 65-67).

The distinction between the two analysis categories developed by Richins et al. (2017) can be made from their distinct starting points. The *theory-driven analysis* begins with a hypothesis; for example, the assumption that a product's appropriate selling price is often found by analyzing its direct and indirect costs. In contrast, *data-driven analysis* begins with the data; for example, fraudulent users and unusual sales trends can be found by studying patterns and relationships in the data. The authors proposed that accountants take charge of theory-driven analysis and data scientists of data-driven analysis. Thus, the authors added that accountants must be prepared to understand and embrace emerging technologies and interact with data scientists to maintain a strong position. I would describe Richins et al. (2017) description of the management accountant's role in business analytics as an analyst of structured data in a divided relationship with data professionals.

Al-Htaybat & von Alberti Alhtaybat, 2017

Al-Htaybat and von Alberti Alhtaybat (2017) interviewed 25 academics and professionals within finance, accounting, and data science about their perceptions of big data in corporate reporting. Although the authors primarily focused on the ambiguous big data concept, they also covered topics related to business analytics. The study's participants considered it necessary for accountants to engage in business analytics. In particular, new technologies were seen as an opportunity to address the timeliness versus reliability conflict of corporate reporting, i.e., that more recent information is preferable but less reliable than old (audited) information. The authors proposed a symbiotic relationship in which accountants focus more on reliability, whereas data scientists focus on timeliness. Therefore, they could complement and enhance each other's expertise. In particular, the authors gave some reasoning for why technology experts will not fully replace accountants:

> […] accountants' tacit knowledge, their approach to decision making, and their inherent values, such as conservatism, reliability, and risk-adversity, must not be eliminated and replaced by statistical analyses and data scientists' analytical approaches since big data needs interpretation and story-telling, which is based on prior knowledge, experience, and theory. (Al-Htaybat & von Alberti-Alhtaybat, 2017, p. 868)

Thus, the authors proposed that "accountants serve as gatekeepers to not only accounting-relevant values but also accounting-based tacit knowledge" (Al-Htaybat & von Alberti-Alhtaybat, 2017, p. 868). I would describe Al-Htaybat & von Alberti Alhtaybat's (2017) description of the management accountant's role in business analytics as a collaborator with data scientists in a collaborative relationship with data professionals.

Barbour et al., 2018

Although not focused on management accounting, Barbour et al. (2018) carried out a study that went deeper into the social aspects of business analytics. The authors interviewed upper-to-middle-level leaders with operational budget responsibilities at a large financial services company trying to implement business analytics. Their findings indicate that business analytics requires creating and managing existing relationships with experts who possess data. In particular, the authors distinguished three distinct interaction patterns between analysis practitioners and technology experts: *requesting* data, *collaborating* to interpret data, and *commissioning* analysis work. The authors explained that *commissioning* required more access, trust, and connections than *requesting* and *collaborating.*

Barbour et al. (2018) indicated that business analytics is often a social practice rather than a technical exercise. The authors stated that analytics "generally involve the relational complications of multidisciplinary knowledge work (e.g., professional identity;

impression management; problems of interpretation, translation, and meaning-making; and organizational politics and struggles for legitimacy)" (Barbour et al., 2018, p. 277). Therefore, they concluded that analysis actors need strategies for navigating relations, power structure, and existing ideas about what analyses ought to produce; for example, filtering information depending on the audience, holding informal conversations, meeting ahead of meetings, and preparing responses to repeated requests. The actors also need a certain degree of freedom to enact such strategies, "to take risks, asking what might seem like odd questions about a project, addressing the project as they saw fit, and exercising their own judgment" (Barbour et al., 2018, p. 278). I would describe Barbour et al.'s (2018) description of the management accountant's role in business analytics as a requestor in a political relationship with data professionals.

2.1.4. Research Question

In the domain theory sub-chapter, I established that business analytics includes tooling, statistics, and mathematics for decision-making and reporting within the context of the data-driven business era (Carillo, 2016; Davenport, 2014). When it comes to the increased analytics orientation of management accounting, I showed that managers had requested business analytics work from management accountants since at least 2013 (Cokins, 2013). But management accountants have been dragging their feet, resisting switching away from Excel and learning business analytics (Oesterreich & Teuteberg, 2019; Schmidt et al., 2020). I theorize that the growth of data scientists into the mainstream (Davenport & Patil, 2012; Baškarada & Koronios, 2017; Avnoon, 2021) could be an answer from the business to the management accountants' intentional self-undermining of not adapting to the business's needs post-2013. I further theorize that the three articles by Richins et al. (2017), Moll & Yigitbasioglu (2019), and Al-Htaybat & von Alberti-Alhtaybat (2017) were an answer to the existential threat when data scientists put the management accountants' jurisdiction under pressure.

Furthermore, I count these three articles, with the addition of Barbour et al. (2018), as the seminal literature for management accounting's collaboration with data scientists in the business analytics domain. I then tried to clarify which roles they propose for management accountants in the business analytics domain and which types of relationships they propose with data professionals. The roles include the evaluator (Moll & Yigitbasioglu, 2019), the analyst of structured data (Richins et al., 2017), the collaborator with data scientists (Al-Htaybat & von Alberti-Alhtaybat, 2017), and the requestor (Barbour et al., 2018). And the types of relationships include the transactional (Moll & Yigitbasioglu, 2019), the divided (Richins et al., 2017), the collaborative (Al-Htaybat & von Alberti-Alhtaybat, 2017), and the political (Barbour et al., 2018).

One of the main gaps I identified in the interdisciplinary business analytics domain was that there were strongly conflicting views on what roles and relationships management accountants would have. In fact, none of the four seminal works that I reviewed agreed with each other. So, I found that the literature is inconclusive on what the increased analytics orientation of management accounting will eventually mean for the management accountants.

The second gap that I identified was that the literature does a bad job of establishing the mechanisms and conditions that would allow management accountants and data scientists to co-exist in an organizational context and jurisdiction that management accountants have historically dominated. Barbour et al. (2018, p. 277) came the closest to this, establishing that it "generally involve[s] the relational complications of multidisciplinary knowledge work (e.g., professional identity; impression management; problems of interpretation, translation, and meaning-making; and organizational politics and struggles for legitimacy." However, I find these arguments too general for determining any practical applications. Therefore, this is another area that could be improved.

With that established, this study aims to identify and evaluate the mechanisms and conditions that allow management accountants and data professionals to co-exist and collaborate in the business analytics domain. The two research objectives I set up were (within the case company context): **RO1:** To identify the roles that management accountants and data professionals play in the business analytics domain. **RO2:** To determine the mechanisms and conditions by which management accountants and data professionals overcome jurisdictional barriers to collaborate in the business analytics domain. And then, the research question followed:

> **Research question:** How do management accountants engage with business analytics, and what role do data professionals play in this process?

With these objectives and the research question, this study aims to contribute to the growing body of knowledge on cross-occupational work between management accountants and data professionals within the business analytics domain. It also aims to help establish how management accounting can maintain its legitimacy in the data-driven business era where management accountants are pressured to become more analytics-oriented but generally lack the skills to perform business analytics efficiently and independently.

2.2. Method Theory

2.2.1. Lenses on occupations and professions in organizations

This thesis will draw upon the three-part conceptual framework for studying occupations and professions developed by Anteby et al. (2016). In the framework, occupations and professions are understood through the three lenses of *becoming*, *doing*, and *relating*. The two lenses of *doing* and *relating* will be of primary focus, as the third lens primarily concerns how individuals are socialized into an occupation. The first of the two, the *doing lens,* is concerned with occupational members' activities. The other, the *relating lens,* regards how occupational members relate to others outside their group. With these two lenses, the aim is to bring different facets of occupations to light and focus attention on specific questions tied to each perspective. As Anteby et al. suggested, studies of cross-occupational coordination can apply a *doing lens* at first that focuses on the conflicts between groups and later transition in the narrative to a relating lens that emphasizes collaboration, specifying the conditions under which conflicts are resolved, and at least temporary partnership is achieved.

The Doing Lens

The *doing lens* suggests that individuals and groups participate in the negotiation and production of work outcomes, jurisdictional boundaries, and structure. An important assumption is that a fixed pie of tasks is divided among various occupations. Therefore, one occupation's gains in task jurisdiction come at another occupation's expense. The *doing lens* focuses on how occupational members perform tasks that have consequences for "individual, occupational, and organizational outcomes (such as shifts in the jurisdiction, status, power, and resource allocation)" (Anteby et al., 2016, p. 200). The *doing lens* is divided into three sub-lenses: *doing tasks*, *doing jurisdictions*, and *doing emergence*.

The sub-lens *doing tasks* is concerned with how workers perform tasks and practices associated with a particular occupation and how these have implications for individual and group outcomes, including identity, meaningful work, and dignity. According to this perspective, workers perform tasks to complete their jobs and enact desired occupational identities. The *doing tasks* sub-lens also considers how workers attempt to reframe or mitigate specific tasks to increase positive identity, the meaningfulness of work, and career outcomes. Tasks that warrant such tactics may be stigmatized because they are seen as morally, socially, or physically tainted, as in "dirty work" occupations (Hughes, 1956, p. 4). Specific tactics include, e.g., reframing, confronting others' perceptions, role-distancing, and gallows humor.

The second sub-lens, *doing jurisdictions*, focuses on "how occupational groups make claims – often against other occupations – to negotiate and change jurisdictional boundaries around the content of their work in an effort to enhance their groups' prestige, influence, and compensation" (Anteby et al., 2016, p. 205). The jurisdiction is the link between a profession and its work. Different occupational groups may engage in jurisdictional contests within organizations, negotiating control, identity, and accountability of tasks. According to this perspective, jurisdictional contests articulate who should do what and what should not be done by whom. The sub-lens also considers how occupational jurisdictions evolve; one occupation's jurisdiction may change, for example, due to the introduction and adoption of new technology.

The final sub-lens, *doing emergence*, homes in on how practices and actions enable the emergence of occupational groups. That is, how groups form to do what is not done by others or do differently what others already do. This phenomenon may take different forms. For example, an occupation may form to take on tasks that another occupation "hives off" (Anteby et al., 2016, p. 208), which may be perceived as menial or of lesser value. Other possibilities include occupations that form as new technologies become widely adopted or if "non-work" activities suddenly become recognized as "work" (Anteby et al., 2016, p. 209).

The Relating Lens

Through the *relating lens*, occupational members are defined by their collaborative relationships with other groups, both occupational and non-occupational (Anteby et al., 2016). Thus, the lens concentrates on understanding "when and how occupational groups collaborate with other groups to perform interdependent work or collectively expand their social influence" (Anteby et al., 2016, p. 212). The authors highlighted that the *relating lens* remedies some of the drawbacks of the *doing lens*. In particular, the *doing lens* does not account for relationships with non-occupational groups such as clients and often tends to overemphasize conflictual or adversarial interactions. The *relating lens* is divided into three sub-lenses: *relating as collaborating*, *relating as coproducing*, and *relating as brokering*.

The *relating as collaborating* sub-lens focuses on collaboration within and between occupational groups. This sub-lens "specifies mechanisms that allow occupational groups to overcome their differences and collaborate to perform interdependent work" (Anteby et al., 2016, p. 214), in stark contrast to how the *doing lens* focuses on jurisdictional conflicts. For example, rules and routines can improve collaboration, team structure can facilitate cross-coordination, and boundary objects, such as engineering drawings and prototypes, can support the translation of meanings and the negotiation of status across occupational boundaries. Another possibility is that shared non-work identities, including race, age, and nationality, can enable cross-occupational collaboration.

The next sub-lens, *relating as coproducing*, widens the scope to consider relationships with all stakeholders with which a group is mutually interdependent. In contrast to the *doing lens*, this perspective considers the pie of tasks as expanding through collaborative action among occupational and non-occupational groups. Thus, occupational expertise is defined by the ability to combine local expertise into a functioning network. For example, a lawyer's relational expertise, such as understanding a judge's behavior, can affect the outcome of civil trials. This perspective seeks to shift attention away from a singular view of occupations. Instead, it suggests that occupations form a network of relations that collectively contribute to building and sustaining their influence. Such a network can, for example, arise from mutual dependency on a particular technology.

The last sub-lens, *relating as brokering*, considers how new occupational groups form as intermediaries to connect networks of people and systems, helping organizations accomplish increasingly interdependent work. Contrary to the *doing lens*, this perspective assumes that "new occupations may emerge to fill critical gaps in complex networks of relations by connecting, buffering, and mediating across multiple organizational and occupational boundaries" (Anteby et al., 2016, p. 218). Rather than compete, such occupations share and coordinate tasks, bridge boundaries, and connect people and tasks to benefit the network.

2.3. Theoretical Framework

It was established in the previous sub-chapters that business analytics could be understood as a multi-disciplinary practice in which its practitioners often must collaborate with data and technology experts (Moll & Yigitbasioglu, 2019; Richins et al., 2017; Al-Htaybat & von Alberti-Alhtaybat, 2017; Barbour et al., 2018). This thesis aims to study how management accountants use these cross-occupational relationships to address problems in business analytics work. To achieve this goal, the conceptual framework for studying occupations and professions developed by Anteby et al. (2016) is used to anatomize the relationships observed during the study. The *doing lens* and the *relating lens* provide two separate perspectives that perhaps each tell part of the story. As Anteby et al. advised, the *doing lens* can be applied first to focus on cross-occupational frictions. Then, the narrative can be shifted to a *relating lens* to emphasize collaboration and specify the conditions that allow the conflicts to be resolved.

To answer the research question, the *doing lens* will be applied to understand what business analytics tasks management accountants do and thus also which tasks they don't do. The *doing lens* will also be applied to understand how management accountants' business analytics work involves data professionals. For example, what tasks do management accountants do, and what tasks do data professionals do that tie into this work? For example, in producing, forecasting, or aiding analysis of data. Then, the thesis will shift the narrative to the *relating lens* to view if and how management accountants use relationships with data professionals to accomplish business analytics work, which tasks, processes, and technologies bring them together, and what strategies they use to bridge cross-occupational tensions. And to look at which stakeholder relationships are tied to business analytics work and which goals and processes are interwoven in these networks.

3. Method

In this chapter, I motivate the research design chosen for the study. I then also briefly present the case company.

3.1. Research Design

An inductive case study combining ethnographic observations with semi-structured interviews was chosen to carry out this study (cf., e.g., Morales & Lambert, 2013; Célérier & Botey, 2015; Tessier & Otley, 2012). Professional jurisdictions and cross-occupational collaboration would be difficult to understand without capturing the surrounding context. Therefore, a case study was suitable for investigating the phenomena within their context and answering the how and why (Lee & Humphrey, 2017).

The ethnographic participant observations functioned as a wide mode of data collection where business analytics activities of management accountants and data professionals could be studied in their natural context (cf. Morales & Lambert, 2013; Becker, 1958; Parker, 2017). Direct observations also made it possible to ask for clarifications, listen to how management accountants and data scientists talked about their work, and observe the general atmosphere online and in-office. After phenomena warranting further research had inductively been identified during direct observation, semi-structured interviews acted as a narrow mode of data collection to zoom in on these phenomena and further develop the inductive reasoning. Thus, the chosen methodology allowed for both wide and narrow data sampling.

After the interviews were carried out, they were transcribed and coded according to an inductive approach. Meeting notes from meetings relevant to the thesis's topic were also coded using the same method. After all the data had been coded, the data was moved into a document database so that the data could be viewed by code or actor.

3.1.1. Participant Observation Details

This study adopted a cross-sectional approach rather than the longitudinal approach typical of participant observation studies. And participant observation data collection was therefore complemented with semi-structured interviews. This modification was necessary because the study was limited in time. In contrast, participant observation research is typically a lengthy process where the researcher is immersed for an extended period to build a longitudinal analysis and diagnosis of the subject (Parker, 2017). Thus, my study adopted a cross-sectional approach rather than the longitudinal approach typical of participant observation studies.

To perform participant observations, the author requested to be hired into the management accounting department's data science team at TechCo. The request was approved, and I could go wander around freely on the premises and in the information systems as a "Thesis Intern." The sole agreed-upon responsibility with the team's manager was that I should write a thesis that could be used as a reference to improve collaboration between the management accountants and data scientists. No conflicts of interest were identified throughout the study. The team's manager gave me free reins for the entire project. All employees I interacted with during the study were briefed about my role when I first talked to them.

The participant observations were carried out from late January to mid-May 2022, primarily through the online video conferencing tool Google Meet. As part of these observations, the author participated in 19 of the data science team's bi-weekly sync meetings where the members' current tasks and blockers were discussed; 20 process sync meetings where various business processes were discussed between data science and management accounting; 4 larger finance department-wide coordination meetings; and 15 individual weekly meetings with the data science team's manager which provided an opportunity to ask questions and discuss the status of the project. Detailed notes were taken in meetings, with the author's reflections added later.

3.2. Case Company

TechCo is a Swedish software technology company. It is a large public enterprise with several thousand employees and revenues upward of ten billion USD. The company is headquartered in Stockholm, with most staff based in Sweden, the US, and the UK. The firm had a functional organizational structure divided into seven business units. The finance department had over a thousand employees split into seven departments; two were the management accounting and finance data engineering departments. The finance data engineering department was the larger of the two, with just over 300 employees. The management accounting department had almost 100 employees.

The company used the communications platform Slack for most internal communication, which allowed employees to jump into conversations with other employees or browse and join channels related to most work processes. Members of different occupations were situated within the same office buildings. So there were places such as social floors or cafeterias which opened for spontaneous meetings. There were no obvious hierarchical boundaries, all employees shared open office landscapes, so there were no offices for managers or anything of that sort. There were also no hierarchical boundaries to communication within the office.

4. Empirics

4.1. Introduction

> In terms of hours saved on the finance side, you know, the [data scientists] pay for themselves a hundred times over, I'm sure. It's definitely a sigh of relief knowing I have the support I have. I'm sure, and I know, every new hire says the same thing. They almost laugh at how supported they are because they feel like they can just reach out for anything, so it's great. (Tom, management accountant)

The management accountants at TechCo were often gracious with their praise for the data scientists in interviews. More than one occupational group was clearly responsible for ensuring that reporting products were churned out efficiently and on time. And the management accountants were undoubtedly happy to receive support. However, it quickly became clear that the dynamics behind this relationship were more complex than they appeared at first sight:

> […] I don't carry the title of a [management accountant]. I'm not technically on their team, and so there's like a little bit of an ownership question, and it's more that I think they are careful about or protective of them being the final word and being the final producer. And in my mind, I think that it doesn't really matter where it comes from. Because I mean, I'm glad for them to review, but if it's my ass on the line and my name attached to it… I'm not out here to get credit; I'm out here to do it the right way. (Ellis, data scientist)

Whereas the management accountants and data engineers had well-established jurisdictional boundaries, the data scientists had to tread more carefully, establish trust, and prove their worthiness to create a jurisdiction grounded on relationships.

This chapter will follow the cross-occupational and cross-departmental reporting processes in which operational and accounting data are turned into decision-making inputs or financial reporting outputs at TechCo. It will center around the management accountants and the actors they interact with, acknowledging that business analytics is a collaborative process (Moll & Yigitbasioglu, 2019; Richins et al., 2017; Al-Htaybat & von Alberti-Alhtaybat, 2017; Barbour et al., 2018). The structure of this chapter begins with an introduction where the case's main actors are presented. Then, the chapter is structured based on the Anteby et al. (2016) framework, beginning with the *doing lens* perspective, staking out jurisdictional claims and potential frictions. Finally, the chapter concludes with the *relating lens* perspective, dealing with how the actors come to terms with each other to create something larger than the sum of its parts.

4.2. The Actors

The TechCo case follows the management accounting department and its close partners as they produce decision-making inputs and financial reporting outputs out of operational and accounting data. The primary actors involved in this process were the management accounting (MA) department, the management accounting data science (DS) team, and the financial data engineering (DE) department. These were not the only actors involved but the most significant. Perhaps a surprising omission was the accounting department. However, the management accountants mainly alluded to working with the accountants when the numbers "look strange" (Grace, management accountant). Therefore, the relationship between the management accountants and the accountants was not considered material from a business analytics standpoint. There was a similar dynamic with other stakeholder groups, such as the legal department and the business unit management teams on the operational side. Therefore, they were also relegated to the supporting cast in this case.

The Management Accounting Department

The management accountants effectively played the role of the final producer in the business analytics domain. The exact responsibilities varied between the different MA teams; however, all units covered by the study played a role in the department's main recurring processes. These included producing rolling 24-month forecasts and accompanying CFO decks, month-end close decks, and long-range forecasts. As part of these routine processes, MA gathered accounting and operational data, consolidated the results, and analyzed the outcomes and outlooks. Eventually, the results made their way to investors and decision makers.

The MA department was generally structured into teams reflecting the business unit structure at TechCo, with each team responsible for controlling one business unit. A central team was then responsible for consolidating the other teams' input into a holistic package. Because of the department's well-established structure and processes, the MA department was perceived as having a relatively rigid role to play in the company: "Reporting and forecasting are always going to happen, everything else is going to be a smaller percentage of people's time" (Ellis, data scientist).

The Management Accounting Department's Data Science Team

The DS team was a new addition, founded roughly thirteen months before the study's inception to support the MA department. It was a small team of three data scientists, but they were in the process of growing with another data scientist and a summer intern. The members had varying backgrounds, with academic degrees in business, statistics, and engineering. However, they had all done data science-related work before joining TechCo within either business or financial settings. Thus, they had more technical profiles compared to most, if not all, management accountants. And they were proficient in skills such as SQL, Python, and Tableau.

The team's role differed significantly from the rest of the MA department. Compared to the relatively entrenched role of the management accountants, the data scientists' task jurisdiction was only loosely defined:

> Given the circumstance of the team, and basically no charter, just a, let's bring in technical people, and they see what they can do, and maybe they'll automate some things and streamline processes. I don't really think the people that hired or developed the idea behind this team knew exactly what we were going to do. And as a result, it created both opportunities and challenges in terms of direction, where if you want to work on something, nothing's stopping you. But you need to spend time building relationships, and you need to learn how to bring something to the table. (Ellis, data scientist)

The team's unclear task jurisdiction was undoubtedly a challenge but not perceived as a losing battle: "And that's why our team has kind of had to insert ourselves a little bit. Or like, be proactive and try to convince people. Which has been going okay actually" (Casey, data scientist).

The data scientists played an intermediary role in the business analytics domain, at the intersection between data engineers and management accountants. At the time, automation and data surfacing made up a large part of their work, but there was a feeling that this was just the tip of the iceberg in terms of what value the team could add in the long run:

> [The management accountants] are so behind in terms of automation that there is just so much to do that you can't really get to the interesting stuff. But I think our team could lean more into the forward-looking kinds of questions in a long-term setting. (Casey, data scientist)

The Finance Data Engineering Department

The DE department lived underneath the finance umbrella as a separate vertical alongside MA and the other finance departments. The data engineers were quickly identified as essential business analytics actors because they effectively produced or handled all the data used by the MA department. They performed the first step of the business analytics process, in which raw data is turned into rudimentary metrics. These metrics then reached the management accountants and data scientists through the ERP or data warehouse, which they also managed. The tools required to process large quantities of data efficiently necessitated that the data engineers had the most technical skillset, as one data engineer alluded to when discussing Scala, Scio, and the various information systems she worked with: "Yes, it's very overwhelming…" (Natasha, data engineer).

Unlike the previous two actors, the engineering department was structured according to Agile (see, e.g., Beck et al., 2001) principles into self-organizing and cross-functional teams. Indeed, the data engineering teams often had members from different occupations, such as product managers, engineering managers, data scientists, and data engineers. They also had some autonomy to decide the team's goals and direction. As Natasha (data engineer) explained: "[…] the team still has some autonomy in the company, so we should be able to define what we want to do." The data engineers generally organized their work into fixed periods called sprints and met, e.g., quarterly for sprint planning to prioritize tasks for the sprint. However, the exact structure varied between teams: "Yeah, we do have sprints-*ish*. We could follow that to a tee if we wanted to. It's very team-dependent on how they want to use these agile tools" (Natasha, data engineer).

These structural and organizational differences resulted in something akin to a cultural barrier between the MA and DE departments:

> […] there will be meetings, and there will be a process by which requirements are defined, that will take some time, there will be prioritization, it may just be that this isn't the right team, it gets moved to another team, and then it'll be scheduled to be worked on in a sprint which could be a month or two later. And so, I think in general, people in finance departments may not be used to or may not have any experience dealing with a product manager or an engineering team that works in this way. (Michael, data scientist)

Several management accountant interviewees gave similar descriptions, explaining that they had difficulties understanding how their requests to the DE department were prioritized. These cultural differences translated into a perceived organizational silo problem. But there had been some recent attempts to lower the barriers between the departments:

> Natasha (data engineer): I think it's probably exactly the same thing the other way around for DE to MA. We also don't have a clear idea of who does what.
>
> Interviewer: Is it almost like a silo?
>
> Natasha: Yeah, I think so. But that's what they're always trying to fix, right? And I think at least now there are some communal Slack channels that have been added recently.
>
> Interviewer: Such as [the finance channel]?
>
> Natasha: Yeah, that didn't exist before. That was very recent. I think it's quite nice because it shakes it up a bit. Like, hey, it's the same organization; it's not completely separate.

4.3. The Jurisdictions of Business Analytics

> Interviewer: Do you find it clear which problems your team should assist the MA department with?
>
> Casey (data scientist): I think it's become more clear. In the beginning, it was very confusing with [the finance data mart DE team]. And to be honest, still, I think that distinction is a bit funky just because they are not creating data. They are also building on top of existing data. And that's sort of what we are doing as well. But I think our use cases are more specific and tailored to specific requests, whereas: "Oh, here's all the [ERP] data dumped." And so, I think MA has caught on to that. But yeah, I would say that that is still sort of fuzzy.

There was some confusion about who should do what within the business analytics domain, even among the primary actors themselves. Interviewees testified to several factors contributing to somewhat unclear boundaries in data work, including the pandemic work-from-home situation, high turnover among managers, and the silo problem between the MA and DE departments. However, the situation was beginning to sort itself out: "Yeah, I think now it's clear. It wasn't as clear in the past, admittedly" (Kay, management accountant). This led me to wonder: Why had the jurisdictions been unclear before, and what had changed? This subchapter aims to clarify these questions from a *doing lens* perspective based on the Anteby et al. (2016) framework while unraveling who does what within the business analytics domain at TechCo.

4.3.1. The Management Accountants' New Jurisdiction

It quickly became apparent that you must follow the data to understand who does what in business analytics. At TechCo, there were effectively two ways that the management accountants accessed data. The first way was through the ERP system, either through a web interface or Microsoft Excel integration. The benefits of this method were that the ERP had a simple user interface where the user could easily control the dimensionality and that reports could be saved to be re-run later. However, the MA department had begun to move away from this method, which led me to refer to it as *the old way*.

Figure 2 represents a simplified model of how data flowed in the reporting process of *the old way*. The black arrow represents data flowing from its sources to investors and decision makers. The double-headed arrow at the bottom indicates that data becomes increasingly structured as it flows from left to right. At the furthest left, the data is in its rawest form. At that point, the data may require cleaning, added dimensionality, or aggregation before it can be used for analysis. The two boxes approximate the jurisdictions of the data engineers and the management accountants, inspired by the *doing jurisdictions* sub-lens of the Anteby et al. (2016) framework. The dotted lines indicate significant stages within the process, beginning with the data ingestion stage. At the ingestion stage, teams within the DE department transport data from its sources to the ERP system. They also clean and structure the data into metrics. From there, the management accountants take over: They collect data from the ERP (the second line), increase the quality further using spreadsheets, create models and analysis using spreadsheets and slide decks (the third line), and finally present the results to investors and decision makers (the final line).

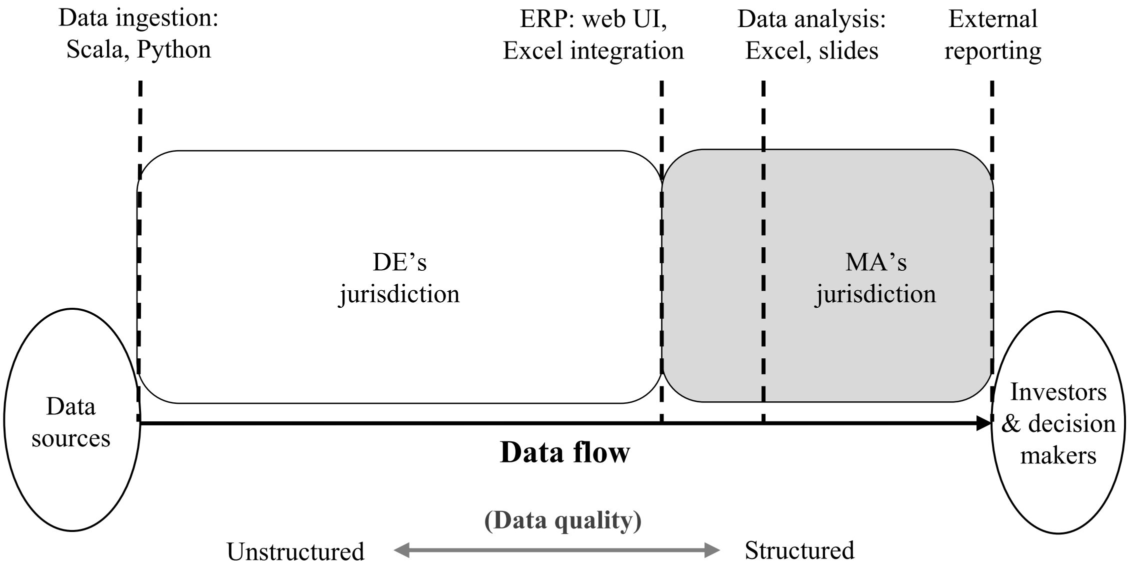

Figure 2. A model of jurisdictions in data work, *the old way.*

So why was *the old way* being phased out? There turned out to be several reasons. During an interview, Grace provided some context to the information system situation at TechCo:

> There is no system that can answer all questions. Not yet, at least. And I don't think there has to be either. It's more about having a palette to choose from rather than having something that can solve everything. (Grace, management accountant)

Grace was referring to the fact that instead of having one extensive integrated system (see, e.g., Oracle, n.d.), TechCo opted to use several commercial and in-house-developed systems in parallel. Each system handled a specific task such as accounting, forecasting, human resources planning, procurement, etc. The systems lacked full integration, so it was a cumbersome and manual process for the management accountants to weave together all the data they needed. Creating these integrations was not an option either, which Grace explained was due to performance limitations of the current ERP:

> [The ERP] is not connected to [the accounting system] in a way that it can be updated automatically in real-time. And it doesn't contain more than the consolidated view, the top line really, for each account. There are no transaction details below. So I can't see anything; I can't even see the provider in [the ERP], nothing. And the reason for this, as I have understood it from Rick, who was the director

of central, so way back, several years ago, was that [the ERP], the performance, would not be able to handle all that stuff. It would simply be too slow. (Grace, management accountant)

Instead of investing in a new ERP, more and more data was transported into a highly performant serverless cloud data warehouse (see, e.g., Google, n.d.). The operational side of the business had already adopted the data warehouse, so data from all parts of the company were accessible from it. As such, both the integration and performance problems of the ERP were circumvented, although some sensitive data was not accessible from the data warehouse. The management accountants had access to more data than before using the data warehouse, and it was steadily growing in usage. Therefore, I refer to this method as *the new way*.

However, switching over to *the new way* was not without friction for the management accountants. Image 3 illustrates how data flows when accessing data using *the new way.* The model is structured similarly to figure 2. The main detail that I want to stress in figure 3 is that the second dotted line, which signifies the handover of data from the DE department to the MA department, is further left than before. The two grey arrows indicate this shift. The data was generally less structured when it reached the management accountants through the data warehouse, requiring more data manipulation work. Adding to this problem, SQL was the primary method of accessing the data warehouse, a skill most management accountants were not proficient with. Thus, management accountants had to do more work and learn new skills. From a *doing jurisdictions* perspective (Anteby et al., 2016), the management accountants' jurisdiction had changed due to the adoption of the new technology.

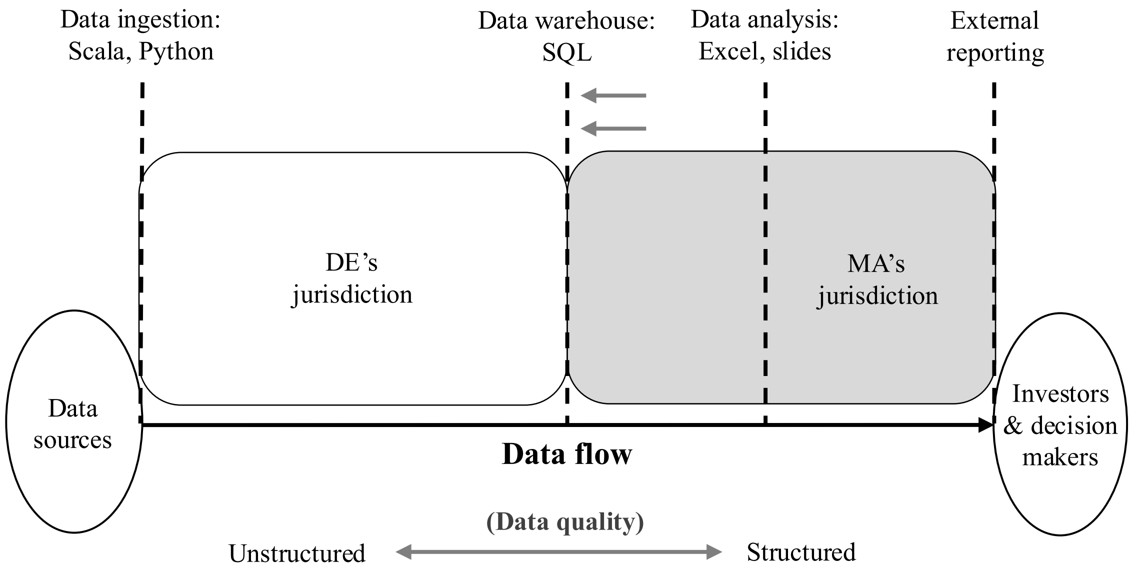

Figure 3. A model of jurisdictions in data work, *the new way.*

4.3.2. Dirty Work

During observations, a now-defunct initiative referred to as the “finance level-up” was brought up (Kim, management accountant). Kim described it as an initiative coming from the top, where all finance personnel had to take online classes to learn SQL. However, Grace, a management accountant who had been part of this initiative, explained sarcastically: “They just sent us to [this website], expecting us to become pros at SQL just like that” (paraphrased). Such discourse appeared to be symptomatic of a perceived lack of support from management for the move to the data warehouse and *the new way*. And, as it turned out, perhaps also symptomatic of disinterest in this new jurisdiction.

After interviewing several management accountants, it became clear which tasks they considered most exciting and important. Or from a *doing tasks* perspective (Anteby et al., 2016), which tasks they felt were consistent with their desired occupational identity. The following account was from Tom:

> […] getting the data should be the easy part. That’s what I like to call *the what* because that’s essentially saying what happened, that’s the variance to forecast or whatever. But then, what people like myself should be really good at and should be able to dig into is *the why*. So it’s saying: “Hey, we were over forecast by 1%.” And then you need to say: “Because of X, Y, Z.” And so that’s the work that is important because those are actionable items, […] that’s the stuff you are providing value with. (Tom, management accountant)

What Tom described as “the why” was also referred to as “storytelling” (Grace, management accountant) or “creating a narrative” (Billy, management accountant) by others. Such tasks were especially gratifying when they involved uncharted territory and the opportunity to “get into the weeds” (Tony, management accountant). From a *doing tasks* perspective (Anteby et al., 2016), such tasks reinforce the desired role, which seemed reminiscent of the increased business orientation of management accounting (see, e.g., Ahrens & Chapman, 2000).

However, as the previous quote from Tom might have alluded to, gathering data was a task that the management accountants were not fond of and considered a chore, taking time away from tasks consistent with the desired occupational identity. These tasks were in the way of identity promoting work and considered lesser in the moral division of labor. The management accountants’ new jurisdiction was seen as dirty work (Hughes, 1956). But perhaps a more fitting name would be *dissonant work* in this case. This opinion appeared widely shared among the management accountants:

> Interviewer: Are some tasks less exciting?
>
> Kay (management accountant): […] anything that involves me doing anything manual does not excite me. Having to download things multiple times, over multiple iterations. Having to tie out and reconcile data when I know I could be doing value-adding tasks.
>
> --
>
> Grace (management accountant): Yes, I have to spend a lot of time extracting information from different systems and compiling them into a third system, in Excel or [the data warehouse] or whatnot (laughing). And what happens is that I spend so much time on it that I don't have much time left for the analysis.
>
> --
>
> Tom (management accountant): If I can spend less time refreshing a data pull so that I can do monthly variance analysis, that's good with me. Analysis is what I am good at. You know, making sure the numbers are right is not as fun. I just wish the numbers were always right.

But it was not only the management accountants that had found themselves with more dirty work (Hughes, 1956). Initially, the data warehouse proved messy; it was hard to find data. Therefore, a team was formed within the DE department to create a finance data mart, collecting the finance function's most used data under one roof within the data warehouse. Though the objective was mainly accomplished, the project seemingly got out of hand. During observations, Kate, a data engineer from the data mart team, explained, "The goal was to use [the finance data mart] as this aggregation of metrics, so it's easy to run different reports out of it. But it grew into something else beyond that." Eventually, the decision was made to scale down the finance data mart to those datasets owned by the team. Because before that, most of the data had not been owned by the team themselves. Instead, they had just been middlemen, providing access or assisting with SQL. Natasha, a data engineer from a separate team, explained that her team wanted to avoid situations like the finance data mart because there was no opportunity to "become a domain expert" or "add value to the datasets." Middleman's work was seemingly considered dirty work by the data engineers (Hughes, 1956).

The combining of the *doing tasks* and the *doing jurisdictions* perspectives (Anteby et al., 2016) led to the construction of figure 4. It is based on the same model as figure 3 but with the added dirty work context (Hughes, 1956). For the management accountants, the dirty work was gathering, cleaning, and verifying data before the final analysis stage, represented by the right-most shaded area. For the data engineers, the dirty work was the middleman work, providing the last line of support for data they did not own themselves, represented by the left-most shaded area. Judging from this model, it should perhaps be no surprise that there was a perceived silo problem between the DE and MA departments; neither party found it consistent with their desired occupational identity to work at the border between their respective jurisdictions.

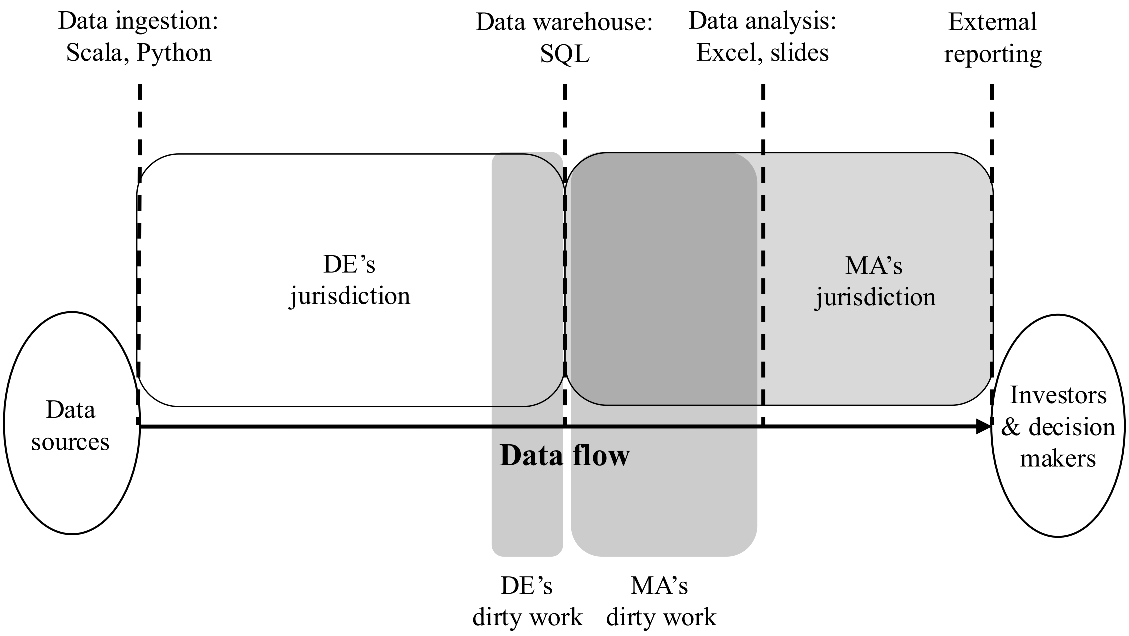

Figure 4. A model of jurisdictions in data work, *the new way*, dirty work (Hughes, 1956) highlighted.

4.3.3. The Missing Link

> But we who are to be involved in the analysis have not received the attention we deserve [from the DE department]. […] So that's what happened. If you don't have it and you get no help, then you build it yourself in the end. So then, we built our own automation team. (Grace, management accountant)

What Grace described was how the MA organization had created its first in-house data science team. (The automation team was the sister team to the current DS team. It later got reorganized into the DE department because one of its projects grew in scale and scope into a de facto engineering project.) As per Grace's account, there was a void to be filled for someone "to set up the systems in a way so [the management accountants could] get more time for analysis," corresponding to the jurisdiction marked as "MA's dirty work" in figure 4.

But it was not only the management accountants that benefitted from the creation of a data science team:

> When the [DS team] was created, before automation was split into the DE department, I know the intention was to not have us bombarding [the DE department] with questions. I think that when [the DS team] was created, the idea was to use DS at the time as the gatekeeper for questions, and then they would handle it with [the DE department]. (Kay, management accountant)

According to the accounts from Grace and Kay, the DS team was seemingly formed so that the MA and DE departments could outsource their dirty work (Hughes, 1956), which is consistent with a *doing emergence* perspective from the Anteby et al. (2016) framework. Combining the *doing emergence* perspective with the *doing jurisdictions* and *doing tasks* perspectives results in figure 5. There are two important details to point out. The first is that the DS team's jurisdiction overlaps the other actors' jurisdictions rather than replacing them. Because although the DS team was created to assist with specific tasks, no formal jurisdictional boundaries were established that stopped the other actors from doing them themselves. The second detail is the dotted line around the DS team's jurisdiction. This reflects the team's mentioned lack of formal jurisdictional boundaries.

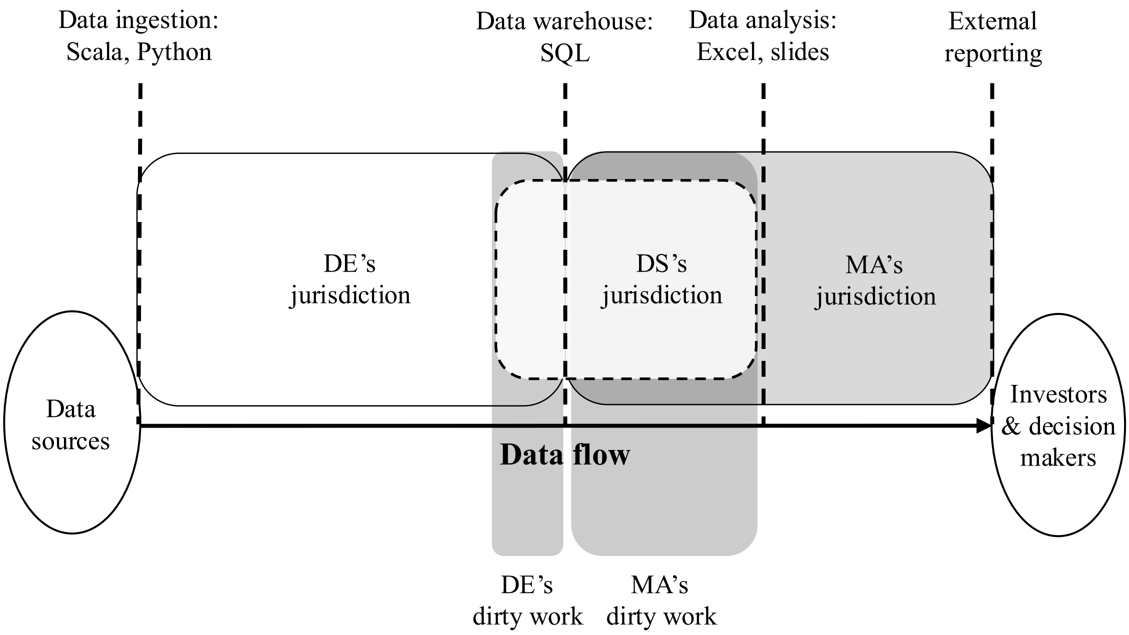

Figure 5. A model of jurisdictions in data work, *the new way*, dirty work (Hughes, 1956) highlighted, with the DS team.

However, there was one problem with the model in figure 5. The *doing lens* assumes a fixed pie of tasks is divided among the actors (Anteby et al., 2016). This assumption is not consistent with the overlapping jurisdictions in the model. When multiple parties claim a jurisdiction, the *doing lens* perspective suggests that negotiation and jurisdictional contests will result in new jurisdictional boundaries (Anteby et al., 2016). However, I found no evidence that the DS team participated in such negotiations and jurisdictional contests. Therefore, I conclude that while the *doing lens* had helped explain *formal jurisdictions*, such as the data engineers' and management accountants', I would have to change my perspective to define the DS team's jurisdiction. So in the next subchapter, I dive deeper into this phenomenon with the help of Anteby et al.'s (2016) *relating lens* perspective to establish what I referred to as the DS team's *informal jurisdiction.*

4.4. The Network of Business Analytics

> Interviewer: How concrete are [MA's] requests?
>
> Michael (data scientist): […] If the job were only to follow well-defined requests, it wouldn't be as challenging or exciting; it would just be writing SQL. So with all that other stuff comes a good background in understanding relationships, slowly changing dimensions, and just data warehousing in general and even analytics or statistics. All of that stuff plays into being able to act as a consultant in certain situations, as a helpdesk in others, as a teacher in others, or as a visualization expert in others.

This quote from Michael explains how the data scientists needed to play different roles in different situations to build and maintain relationships with the management accountants. Sometimes this meant acting as a consultant, assisting with "deeper analysis […], layering in additional data to figure out drivers" (Ellis, data scientist). Or as a helpdesk, helping to write "sample queries" or "surface data" (Casey, data scientist). Or as a "translator or liaison," bridging between the DE and MA departments (Casey, data scientist). Or as a teacher, "training the team, upscaling people, and enabling them to self-serve [from the data warehouse]" (Michael, data scientist).

These roles had one thing in common–they all filled critical gaps in a network of people and systems (see, e.g., Latour, 1992 on actor-network theory). Figure 6 illustrates the same process as figures 3-5 but this time represented as a network graph inspired by actor-network theory and the *relating lens* perspective from the Anteby et al. (2016) framework. Dotted lines represent the weaker links in the network. They represent the management accountants' lower proficiency in using the data warehouse and the silo problem between the MA and DE departments. From a *relating as brokering* perspective, intermediaries such as the DS team enable organizations to accomplish interdependent work by filling in weaker links (Anteby et al., 2016). In this model, the DS team forms a connection between the MA department and the data warehouse by helping the management accountants access data, whether as a "consultant," a "helpdesk," or a "teacher" (Michael, data scientist). They also bridge the MA and DE departments in their capacity of "translator or liaison" (Casey, data scientist) or even project manager:

> Being a data team within MA, we can immediately assess [requests from the management accountants]. We can know if it requires an engineering team to do some work on it, loop them in, and manage that project. Or if it's something easy, then, "Here you go, it's done." (Michael, data scientist)

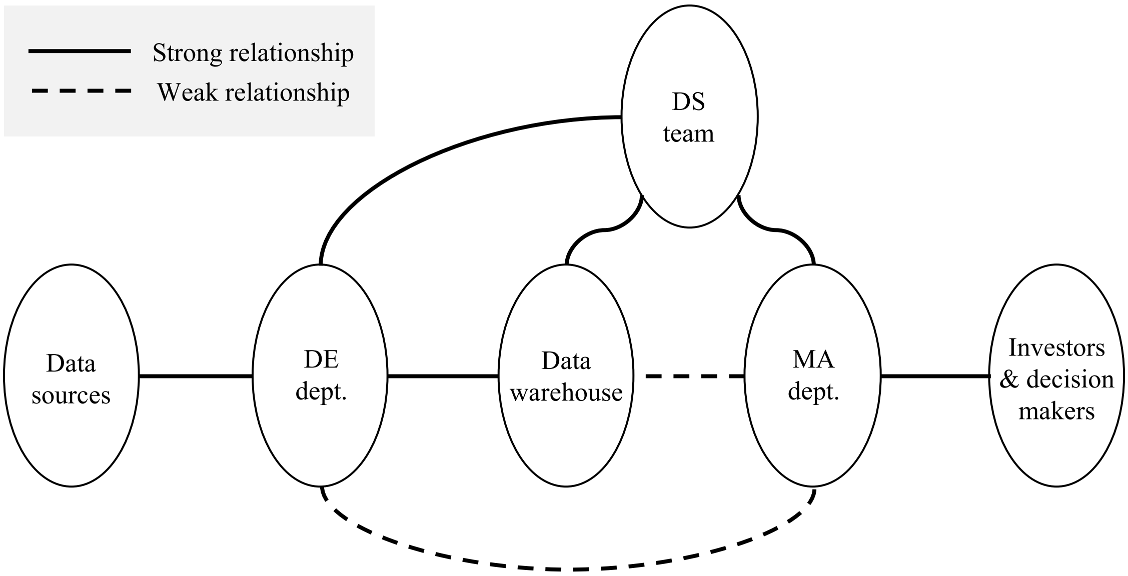

Figure 6. A network graph representation of data work, *the new way*.

4.4.1. An Informal Jurisdiction Based on Relationships

By combining the *relating as brokering* and *doing jurisdictions* perspectives, we can form the idea of *informal jurisdictions*: If an actor earns enough trust as an intermediary in a network and can prove that it is more beneficial to go through them than not, then people will mostly do so. Therefore, even if the data scientists' jurisdiction was unclear and overlapped with the management accountants' and data engineers', they could establish a de-facto jurisdiction by being the path of least resistance. However, the data scientists needed to develop solid relationships and prove their worth to be seen as such. This gives further context to the quote: "And that's why our team has kind of had to insert ourselves a little bit. Or like, be proactive and try to convince people. Which has been going okay actually" (Casey, data scientist). Or how Ellis described "leaning in" and "pushing back" to find a sweet spot and establish trust:

> […] the second thing is just being comfortable with maintaining relationships and pushing back where I need to, leaning in where I want to or think is best. And so, because of that, they see me as sort of an extension of their team. Which is helpful because it signifies trust. (Ellis, data scientist)

The key to the relationship between the management accountants and data scientists was mutual benefit. In this exchange, the data scientists lent their skills to the management accountants, enabling them to become more data-driven and allowing them to spend more time on desirable work. In return, the data scientists could procure work from the management accountants, build a reputation, and eventually establish *informal jurisdiction*.

There was also an assumption among the data scientists that stronger relationships result in more exciting work. Therefore, the data scientists did not necessarily see lower-analysis-content work, such as assisting with data requests, as dirty work, contrary to the management accountants. Instead, they were seen as opportunities to get exposure, create relationships, establish trust, and learn more about the business domain. By taking on less-analytical work, they could position themselves where opportunities for more exciting work could materialize at a later stage. Ellis (data scientist) described finding these opportunities as akin to a "you don't know what you don't know situation." Implying that a set of more technical eyes could often find exciting work that was overlooked by the management accountants. But opportunities for work could also be found mutually through conversations:

> I'm not a data person, hands up. I'm going to admit that, and if I explain what I'm using that data for, sometimes that's where the ideas come out. You ask, you know, "Is it clear when DS can step in and be a useful resource?" And a lot of times, I don't know until situations come about where we are in a conversation together. (Billy, management accountant)

5. Discussion

5.1. Introduction

This thesis aimed to study how management accountants engage with business analytics and what role data professionals play in this process. The literature argues that business analytics is a social and interdisciplinary phenomenon undertaken through a collaboration between data professionals and management accountants (Moll & Yigitbasioglu, 2019; Richins et al., 2017; Al-Htaybat & von Alberti-Alhtaybat, 2017; Barbour et al., 2018). This thesis's main contribution to this body of literature highlights the critical role that data scientists can play in filling in the weak links in the business analytics network (see figure 6 above) between management accountants, data engineers, and a data warehouse.

The data scientists are generalists, as argued in the literature (Baškarada & Koronios, 2017). Therefore, the intermediary role suits them because they can adjust to the network's needs, whether a consultant, helpdesk, liaison, or teacher is needed. They avoid jurisdictional competition with the other actors by relying on relationships and *informal jurisdiction*. These factors enable them to act as the *connective tissue* of the business analytics network. The short answer to the research question is that management accountants engage with business analytics through a network of different actors. The main business analytics actors include the data engineers who move, clean, and structure data into metrics; the data warehouse, that stores data from the entire company but requires technical skills to interact with; the management accountants, who analyze and tell stories about data; and finally, the data scientists, who play different roles in different relationships to link it all together.

5.2. Business Analytics at TechCo

The literature suggests that management accountants are pressured to become more analytics-oriented (Cokins, 2013). However, it also indicates that management accountants lack the business analytics skills to take advantage of such opportunities (Oesterreich & Teuteberg, 2019; Schmidt et al., 2020). The analysis supports both these arguments, adding that these two contradicting phenomena can cause tensions when a data warehouse is implemented to replace the ERP for accessing data. At TechCo, the data warehouse was meant to improve the department's analytical capacity, but the management accountants initially lacked the skills to utilize the data warehouse efficiently. The result was a disconnect between the management accountants and the data—the opposite of the data warehouse's purpose. As a result, the management accountants had to spend more time cleaning and verifying data which they considered dirty work (Hughes, 1956). When they instead could have been doing their identity-promoting analysis and storytelling work.

The management accountants tried to ease the transition by relying on a team of data engineers for data requests. This was similar to Barbour et al.'s case study (2018), where the analysts relied on external experts for data requests. However, unlike their research, the analysis suggests that the middleman work of finding data and writing database queries for the management accountants was generally considered dirty work (Hughes, 1956) by TechCo’s data engineers. Shielding the data engineers from questions was later expressed as one of the reasons why the management accounting department created its own data scientist team. So why could the analysts leverage external data experts in Barbour et al.'s case, whereas, at TechCo, they had to create their own support function? The main difference between the two studies is that Barbour et al. only followed the very beginning of the organization’s business analytics efforts. Whereas with TechCo, I was able to gain data relating to a more extended period. I believe that the differences could be related to the time it takes for jurisdictional boundaries to solidify after they change due to technology adoption or process innovation (Anteby et al., 2016). The actors may be more flexible and willing to help, as in Barbour et al.’s case, before jurisdictional boundaries have been negotiated and decided upon (Anteby et al., 2016). But the difference could also be due to moderating factors. For example, Barbour et al.’s case company appeared more hierarchical, meaning that data engineers potentially did not have the agency to decline the requests. I leave this topic open for further research.

At TechCo, the data disconnect problem led the management accounting department to create its own data science team to act as an intermediary between it, the data warehouse, and the data engineers. This is close to Al-Htaybat & von Alberti-Alhtaybat’s (2017) perspective on collaboration between accountants and data scientists, who suggested that they “form multidisciplinary teams that complement and enhance each other's expertise.” But, in TechCo’s case, they created a separate data science team within the department instead of inserting data scientists straight into the respective management accounting teams. I speculate that this decision allowed for knowledge sharing between the data scientists; however, I leave whether to distribute or centralize data scientists within the management accounting organization as another topic for further research.

However, the data scientists’ role as an intermediary contradicts Moll & Yigitbasioglu’s (2019) perspective on collaboration between accountants and data scientists. They argued for a disjoint transactional relationship where accountants contribute to “the evaluation, implementation, and maintenance” of business analytics. They also argued that data scientists might increasingly challenge accountants’ jurisdiction. Neither argument was substantiated at TechCo, the management accountants and data scientists founded joint collaborative relationships, and there were no signs of jurisdictional conflict. It is hard to determine why the results were different because Moll & Yigitbasioglu did not motivate these arguments in detail.

The data scientists' role as an intermediary also contradicts Richins et al.'s (2017) perspective on collaboration between accountants and data scientists. Richins et al. conceptualize that data scientists and management accountants each have a comparative advantage, data scientists a technical advantage, and accountants a domain knowledge advantage. Therefore they suggest a division of labor based on data quality, where data scientists analyze unstructured data and accountants analyze structured data. However, in the case of TechCo, the data scientists' role was best described as a link between the management accountants, data engineers, and data warehouse, not in terms of tasks or data quality. I believe that Richins et al. arrive at their conclusion because they view the relationship between accountants and data scientists more from a *doing lens* perspective, according to Anteby et al.'s (2016) framework. The division they suggest could be a valid option for splitting the business analytics jurisdiction from a *doing lens* perspective. Management accountants handle structured data problems, and data scientists handle unstructured data problems.

However, I see two problems applying Richins et al.'s (2017) framework to my data. First, it would mean that the management accountants have to yield some of their jurisdiction to the data scientists, which creates a risk of jurisdictional competition (Anteby et al., 2016). Second, according to my data, the requestors of business analytics are the investors and decision makers. They come to the management accountants with a question, for example: What was the outcome in market X in July? They don't go to them with a dataset and say: Here is some unstructured data. So, for Richins et al.'s framework to be applicable, the requestors must know whether a question requires structured or unstructured data to direct it to the correct actor. This would be feasible for the question about the market outcome. However, it is harder to tell which data would be needed to answer the question: Should we enter market Y? It should be noted that Richins et al. (2017, p. 75) do encourage "future research to examine the empirical validity of our recommendations." And with my data, I refute the validity of their framework as far as the context of this case goes.

The final contribution I make is that the data scientist team relied on what I refer to as *informal jurisdictions.* According to the data, the data science team did not make any formal jurisdictional claims (Anteby et al., 2016). The data scientists used their unclear jurisdiction as an advantage to avoid jurisdictional conflicts with the well-established management accountant and data engineer groups. The data scientists' relationships with the management accountants would presumptuously be drastically different if they expressed: All data warehouse analytics must be approved by us! Instead, they relied on *informal jurisdictions*: If an actor earns enough trust as an intermediary in a network and can prove that it is more beneficial to go through them than not, then people will mostly do so. The data scientists become an indispensable link and establish a de-facto jurisdiction within the context of their role as an intermediary. These relationships often began with small steps; less-analytical work was seen as an opportunity to get exposure, create relationships, establish trust, and learn more about the business domain. By taking on less-analytical work, the data scientists could position themselves where opportunities for more exciting work could materialize later.

I see *informal jurisdictions* as a small contribution to a minor gap in the Anteby et al. (2016) framework. It is a compromise between the overly selfish *doing jurisdictions* perspective and the overly selfless *relating as brokering* perspective. To clarify the concept, I will try to list the necessary conditions:

1. An established relationship between two actors (humans or nonhumans).
2. A new actor (human or nonhuman) can intermediate the established relationship.
3. The intermediary is preferable to the established relationship.
4. The intermediary has something to gain from intermediating.
5. The intermediary establishes trust and reputation with the actors.

One example could be:

1. There is a river I have to swim across to get from home to work.
2. One day, someone builds a bridge across the river.
3. The bridge saves me 30 minutes of swimming (I don't like swimming).
4. The bridge has advertising billboards that pay per crossing.
5. Over the next couple of days, I test the bridge and found that it is safe and quick.

Unless I feel like swimming, I will now take the bridge to work every time. The bridge's owner is also happy because of the advertising money. The bridge owner now controls the process in which I will cross the river; she has *informal jurisdiction*. But she cannot stop me from crossing the river in another process, such as swimming, so she does not have formal jurisdiction. But swimming has become pointless with the bridge, so it is a de-facto jurisdiction.

5.3. Moderating Factors

The contributions must be understood within the context of the case's setting. In particular, several moderating factors must be considered. For example, the nature of the case company. As a software technology company, the concept of data scientists would be more established at TechCo than at a company in another industry. Data scientists are well-established actors in software product research. It is possible that the management accounting department's data scientist team at TechCo inherited some legitimacy because of the company context. Therefore, it could be more difficult for data scientists in another industry to build similar relationships, especially if the data scientist occupation is not a familiar concept there.

Another factor was that the data engineers, data scientists, and management accountants worked underneath the same roof at TechCo. At least those located in the same region. This makes it easier to form relationships because of the possibility of meeting face-to-face and having impromptu meetings. This is especially compared to an organization with a silo structure where separate departments don’t share office space. However, the pandemic and mandated work-from-home situation lessened the impact of this factor. Note that the opposite could also be true: the work-from-home situation could reduce the generalizability as the workforce returns to the office.

The third moderating variable was related to the low barriers to communication at TechCo. The Slack messaging platform allowed employees to jump into conversations with other employees or browse and join channels related to most work processes. The ability to read historical discussions related to work processes was likely a significant factor because it enables transparency and stops actors from gatekeeping information. Therefore, the low barriers to communication were likely a critical enabler for the data scientists to tune into the other actors’ processes.

Finally, loose leadership enabled the data scientist team to operate within an unclear jurisdiction. The team was given general goals but no formal jurisdictional boundaries. The results would be impossible to replicate in a hierarchical organization with strict directives and boundaries. Because without unclear jurisdictional boundaries, there would be jurisdictional competition, and the data scientists would not be able to collaborate with the management accountants within their jurisdiction (Anteby et al., 2016).

Overall, I acknowledge that any variable that would make it more challenging to establish cross-occupational relationships could make it harder to reproduce the results. Unfortunately, it is impossible to confirm if I caught the most important ones, which is one of the limitations.

5.4. Limitations

I acknowledge certain limitations with the study, including the scope. The single case study format limits my confidence in identifying every moderating factor. Therefore, there could be unknown contextual variables that drove the results.

Another limitation is that I only performed twelve interviews. But I believe my direct observations alleviated this problem. During my observations, I could ask for clarifications, listen in to how management accountants and data scientists talked about their work, and observe the general atmosphere both online and in-office. This allowed me to interpret the results better and ask the right questions. However, I acknowledge that the information saturation could have been even stronger if I had done more interviews.

The actors I interacted with knew about my role as an observer, which may have influenced my interactions with them. However, the research question was not seen as controversial by the employees. I also had well-established relationships with several employees from previous internships and noticed no differences compared to previous interactions. For these two reasons, I believe the consequences of reflexivity were negligible.

5.5. Practical Applications

The main contribution to the field is the concept of data scientists as an intermediary that can fill in weak links between other actors and technology in the business analytics network, see figure 6 above. The *informal jurisdictions* concept makes it possible to create a data scientist team without disturbing existing jurisdictional boundaries, i.e., status quo. For example, if an organization wants to adopt a new business analytics technology or process but acknowledges that the current employees do not have the skills necessary. Yet the employees would be happy to receive help if they do not lose jurisdiction. Then it can make sense to recruit a team of data scientists, tell them to assist with the adoption, and give them free reins. The data suggest they would insert themselves where it pays off to create relationships and find more exciting work.

In a generalized setting, the intermediary and *informal jurisdiction* concepts can be applied to situations where there is a need to fill in weak links between actors in a network, but you want to avoid jurisdictional conflicts. Similar results should be expected as long as the listed conditions are fulfilled.

The main caveats to both applications are the moderating factors and any hinders to communication or forming relationships, including gatekeeping information, organizational silos, high barriers to communication, or strict hierarchies. These factors would make it harder to reproduce the results.

5.6. Future Research

Two interesting topics for further research came up when discussing the results. The first topic was to what degree jurisdictional boundaries (Anteby et al., 2016) are flexible after adopting new technology or processes. When comparing my data to Barbour et al. (2018), I theorized that our results differed because Barbour et al. studied an organization shortly after they implemented business analytics. In contrast, I studied an organization that had time to settle down. It could be interesting for future research to establish if, or for how long, jurisdictional boundaries are flexible. And the dynamics behind flexible boundaries.

The second topic was whether to distribute data scientists in multidisciplinary teams with management accountants as suggested by Al-Htaybat & von Alberti-Alhtaybat (2017) or to centralize them as TechCo. This question could impact the direction of management accounting. What jurisdiction (Anteby et al., 2016) do data scientists have when they are part of management accounting teams? Do they compete for jurisdiction with the management accountants? Is it possible to apply the concept of *informal jurisdictions* in a distributed setting too? Which alternative is best, and what are the pros and cons?

The concept that business analytics depends on a network of relationships between actors and systems has some interesting consequences. Especially when the entire business analytics network at TechCo was dependent on the intermediary role played by data scientists. With this dependence on relationships, how dependent exactly is business analytics on soft skills, politics, and cultural controls? A follow-up question is whether it's possible to design the data scientists' team composition to engineer good relationships. Which backgrounds are the most compatible, or is a mix required? Can the management accountants be involved in the hiring process to ensure it's a fit on both sides?

The other logical line of questioning is how sensitive the business analytics network is to employee turnover. Is the data scientists' reputation individual or team-based? Would it be possible to establish a brand or reputation for the team so that business analytics becomes less dependent on individuals? If the team can create a brand, would some data scientists begin focusing on reputation building while others concentrate on tasks? And would it be possible to implement a succession planning mechanism in these relationships?

6. Conclusion

This thesis aimed to study how management accountants engage with business analytics and what role data professionals play in this process. Management accountants engage with business analytics through a network of different actors. The main business analytics actors include the data engineers who move, clean, and structure data into metrics; the data warehouse, that stores data from the entire company but requires technical skills to interact with; the management accountants, who analyze and tell stories about data; and finally, the data scientists, who play different roles at different times to strengthen weak links in the network.

This thesis's main contribution to the interdisciplinary business analytics domain highlights the critical role that data scientists can play in bridging weak links in the business analytics network between management accountants, data engineers, and a data warehouse (see figure 6 above). The intermediary role suits the generalist data scientists well because they can play several roles based on the network's needs. For example, a consultant role, assisting the management accountants with deeper data analysis. Or a helpdesk role, helping to write queries or find data. Or a liaison role, enabling the communication between the data engineering and management accounting departments. Or a teacher role, training the management accountants and enabling them to self-serve from the data warehouse.

The data scientists avoided jurisdictional conflicts with the more established actors because they had a loosely-defined jurisdiction centered around assisting the other actors with data work. Instead of making formal jurisdictional claims, the data scientists relied on *informal jurisdictions*. These were gained by positioning themselves as indispensable intermediaries in the business analytics network. These relationships often began with small steps; less-analytical work was seen as an opportunity to get exposure, create relationships, establish trust, and learn more about the business domain. By taking on less-analytical work, the data scientists could position themselves where opportunities for more exciting work could materialize later.

Several moderating factors were considered. First, data scientists are a familiar concept in software technology companies. Second, actors from all occupations shared the same offices, enabling relationship building. Third, there were low barriers to communication and high process transparency, enabling data scientists to tune into other actors' work more efficiently. Finally, loose leadership translated into the data scientists' loosely-defined jurisdiction, letting them circumvent jurisdictional conflicts.

Several limitations were also acknowledged. The first was the scope; the single case study format made it harder to identify moderating factors. The second was that only twelve interviews were performed. However, data was also gathered through direct observations, which alleviated the problem. The third was that the actors knew about my role as an observer, which may have influenced my interactions with them. However, the topic was not seen as controversial, and I had previously-established relationships from internships and noticed no differences compared to previous interactions.

Four potential areas for future research came up during the study. First, are jurisdictional boundaries flexible for a period after adopting new technology or processes? Second, when the business analytics network depends on relationships between actors, how dependent are business analytics on soft skills, politics, and cultural controls? Third, with the same context as the second question, how sensitive is the network to employee turnover? And fourth, whether to centralize or distribute data scientist resources in the management accounting organization.

7. Appendix

7.1. Appendix A. Overview of Conducted Interviews

#	Pseudonym	Occupation	Length	Date
1 (i)	Michael	Data scientist	60 minutes	Feb 2022
2	Kay	Management accountant	60 minutes	Apr 2022
3	Tom	Management accountant	60 minutes	Apr 2022
4 (ii)	Michael	Data scientist	60 minutes	Apr 2022
5	Grace	Management accountant	60 minutes	Apr 2022
6	Gary	Management accountant	60 minutes	Apr 2022
7	Casey	Data scientist	60 minutes	Apr 2022
8	Billy	Management accountant	60 minutes	Apr 2022
9	Kim	Management accountant	60 minutes	May 2022
10	Natasha	Data engineer	60 minutes	May 2022
11	Ellis	Data scientist	60 minutes	May 2022
12	Tony	Management accountant	60 minutes	May 2022

8. Bibliography

Ahrens, T., & Chapman, C. S. (2000). Occupational identity of management accountants in Britain and Germany. European Accounting Review, 9(4), 477-498.

Al-Htaybat, K., & von Alberti-Alhtaybat, L. (2017). Big Data and corporate reporting: impacts and paradoxes. *Accounting, Auditing & Accountability Journal, 30*(4), 850-873.

Anteby, M., Chan, C. K., & Dibenigno, J. (2016). Three Lenses on Occupations and Professions in Organizations. *The Academy of Management Annals, 10*(1), 183-244.

Appelbaum, D., Kogan, A., Vasarhelyi, M., & Yan, Z. (2017). Impact of business analytics and enterprise systems on managerial accounting. *International Journal of Accounting Information Systems, 25*, 29-44.

Arnaboldi, M., Busco, C., & Cuganesan, S. (2017). Accounting, accountability, social media and big data: revolution or hype? *Accounting, auditing & accountability journal , 30*(4), 762-776.

Avnoon, N. (2021). Data Scientists' Identity Work: Omnivorous Symbolic Boundaries in Skills Acquisition. *Work, Employment and Society, 35*(2), 332-349.

Barbour, J. B., Treem, J. W., & Kolar, B. (2018). Analytics and expert collaboration: How individuals navigate relationships when working with organizational data. *Human Relations, 71*(2), 256-284.

Baškarada, S., & Koronios, A. (2017). Unicorn data scientist: the rarest of breeds. *Program, 51*(1), 65-74.

Beck, K., Beedle, M., Van Bennekum, A., Cockburn, & Alistair. (2001). *The agile manifesto*.

Becker, H. S. (1958). Problems of Inference and Proof in Participant Observation. *American Sociological Review, 23*(6), 652-660.

Carillo, K. D. (2016). Let's stop trying to be "sexy" preparing managers for the (big) data-driven business era. *Business Process Management Journal, 23*(3), 598-622.

Célérier, L., & Botey, L. E. (2015). Participatory budgeting at a community level in Porto Alegre: a Bourdieusian interpretation. *Accounting, Auditing & Accountability Journal , 28*(5), 739-772.

Cokins, G. (2013). Top 7 trends in management accounting. *Strategic Finance, 95*(6), 21-30.

Davenport, T. H. (2014). *Big data at work: dispelling the myths, uncovering the opportunities.* Harvard Business Review Press.

Davenport, T. H., & Patil, D. (2012). Data Scientist: The Sexiest Job of the 21st Century. *Harvard Business Review, 9*, 70-76.

Google. (n.d.). *BigQuery*. https://cloud.google.com/bigquery

Hall, M., Mikes, A., & Millo, Y. (2015). How do risk managers become influential? A field study of toolmaking in two financial institutions. *Management Accounting Research, 26*, 3-22.

Hughes, E. C. (1956). Social role and the division of labor. *Canadian Journal of Economics and Political Science, 18*(2), 3-7.

Latour, B. (1992). Where are the missing masses? The sociology of a few mundane artifacts. In W. E. Bijker, & J. Law, *Shaping technology/building society: Studies in sociotechnical* (pp. 225-258). MIT press.

Lee, B., & Humphrey, C. (2017). Case studies in accounting research. In Z. Hoque, L. D. Parker, M. A. Covaleski, & K. Haynes, *The Routledge Companion to Qualitative Accounting Research Methods* (pp. 163-183). Routledge.

Moll, J., & Yigitbasioglu, O. (2019). The role of internet-related technologies in shaping the work of accountants: New directions for accounting research. *The British Accounting Review, 51*(6), 100833.

Morales, J., & Lambert, C. (2013). Dirty work and the construction of identity. An ethnographic study of management accounting practices. *Accounting, Organizations and Society, 38*, 228-244.

Oesterreich, T. D., & Teuteberg, F. (2019). The role of business analytics in the controllers and management accountants' competence profiles An exploratory study on individual-level data. *Journal of Accounting & Organizational Change, 15*(2), 330-356.

Oracle. (n.d.). *Oracle Enterprise Resource Planning (ERP)*. https://www.oracle.com/erp/

Parker, D. L. (2017). Participant observation at the coalface. In Z. Hoque, L. D. Parker, M. A. Covaleski, & K. Haynes, *The Routledge Companion to Qualitative Accounting Research Methods* (pp. 339-353). Routledge.

Quattrone, P. (2016). Management accounting goes digital: Will the move make it wiser? *Management Accounting Research, 31*, 118-122.

Richins, G., Stapleton, A., Stratopoulos, T. C., & Wong, C. (2017). Big data analytics: Opportunity or threat for the accounting profession? *Journal of Information Systems, 31*(3), 63-79.

Tessier, S., & Otley, D. (2012). From management controls to the management of controls. *Accounting, Auditing & Accountability Journal, 25*(5), 776-805.