Tampere University

Tuomas Jalonen

MANAGEMENT ACCOUNTING INFORMATION IN DECISION-MAKING: UNVEILING POSSIBILITIES FOR AI

Faculty of Engineering and
Natural Sciences
Master of Science Thesis
November 2019

ABSTRACT

Tuomas Jalonen: Management Accounting Information in Decision-Making: Unveiling possibilities for AI
Master of Science Thesis
Examiner: Professor Teemu Laine
Examiner: Postdoctoral Research Fellow Tuomas Korhonen
Faculty of Engineering and Natural Sciences
Tampere University
Degree Programme in Mechanical Engineering
November 2019

Despite the great opportunities of artificial intelligence (AI) in decision-making, the combination has been neglected among management accounting researchers. A qualitative multiple case study was used to address the issue within four case companies and eleven semi-structured interviews. The cases cover production forecast, sales targeting, productivity investment and target setting decisions.

As a result, I suggest a new data accountant role, who acts as a translator between AI and managers. He/she translates the needs of managers to AI and then explains the results and logic to the managers.

Major limitation is that AI was not used in the cases, which makes this study more future-oriented. More research, especially practical cases on decision-making with AI, is needed. For managers, this thesis underlines that accounting and AI have many other roles than just giving answers, and they have to be actively managed in order to promote healthy decision-making culture.

Keywords: artificial intelligence, decision-making, management accounting

TIIVISTELMÄ

Tuomas Jalonen: Laskentatieto päätöksenteossa ja tekoälyn tarjoamat mahdollisuudet
Diplomityö
Tarkastaja: Professori Teemu Laine
Tarkastaja: Tutkijatohtori Tuomas Korhonen
Tekniikan ja luonnontieteiden tiedekunta
Tampereen yliopisto
Konetekniikan tutkinto-ohjelma
Marraskuu 2019

Vaikka tekoäly tarjoaa suuret mahdollisuudet päätöksenteon tukemiseen, yhdistelmää on tutkittu varsin vähän johdon laskentatoimen alueella. Vastatakseni tähän tutkimustarpeeseen, käytin laadullista monitapaustutkimusta aineiston koostuessa neljästä yrityksestä ja yhdestätoista puolistrukturoidusta haastattelusta. Tapaukset ovat tuotantoennusteen laadinta, myynnin kohdistaminen, tuottavuusinvestointi sekä tavoiteasetanta.

Tuloksena esitän uuden data accountant -roolin, joka toimii tekoälyn ja johtajien välissä. Hän tulkitsee johtajien tarpeet tekoälylle, ja selittää sen antamat tulokset takaisin johtajille. Lisäksi esitän roolille prosessikuvauksen.

Suurena rajoitteena on, että yhdessäkään tapauksessa tekoälyä ei käytetty päätöksenteossa. Lisätutkimusta tarvitaan etenkin käytännöllisistä tapauksista, joissa tekoälyä aidosti hyödynnetään päätöksenteossa. Johtajille tämä työ toimii muistutuksena siitä, että laskentatoimella ja tekoälyllä on useita eri rooleja pelkkien vastausten antamisen lisäksi, ja niitä tulee johtaa aktiivisesti terveen päätöksentekokulttuurin tukemiseksi.

Avainsanat: tekoäly, päätöksenteko, johdon laskentatoimi

Tämän julkaisun alkuperäisyys on tarkastettu Turnitin OriginalityCheck –ohjelmalla.

PREFACE

First, I would like to express my gratitude to Teemu Laine and Tuomas Korhonen for guiding me through this thesis project. Second, I would like to thank everyone in Cost Management Center research group for the fun work environment and for your everlasting support. Thank you (in alphabetical order) Deborah, Jari, Joonas, Jouni, Leo, Maria, Natalia, Olli, Riku, Teemu, Tommi, Tuomas and Vesa. Third, I would like to express the deepest appreciation to all my friends inside and outside of academia for being my friends. Fourth, I would like to thank all the case companies and informants for your time and Business Finland for funding this project.

Although I am about to become a Master of Science, the five years at the university have taught me, that mastering science completely is unfortunately impossible. Despite the limitations, one can still be one’s own master, and maybe even a master of a tiny part of science. Thus, probably the most important outcome of my education has been learning how to learn and how important it is to keep learning and mastering new skills continuously. Finally, I would like to give some advice to future me: if you do not regret anything that you did half a year ago, you have not been learning fast enough.

Tampere, 20 November 2019

Tuomas Jalonen

CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF SYMBOLS AND ABBREVIATIONS

ABCM	Activity-Based Costing Management
AI	Artificial Intelligence
AIS	Accounting Information System
ANT	Actor-Network Theory
BD	Big Data
BI&A	Business Intelligence and Analytics
BSC	Balanced Scorecard
BU	Business Unit
CAD	Computed-Aided Design
CAM	Computer-Aided Manufacturing
DMAIC	Define, Measure, Analyze, Improve and Control
HR	Human Resources
MA	Management Accounting
MAS	Management Accounting System
MCS	Management Control System
NLP	Natural Language Processing
NN	Neural Network
NPD	New Product Development
PMS	Performance Measurement System
P&L	Profit and Loss Statement
R&D	Research and development
RS	Rough Set Theory
SME	Small and Medium-sized Enterprise
R^2	Coefficient of determination

1. INTRODUCTION

1.1 Background and motivation

The public interest towards artificial intelligence (AI) has increased rapidly in the 2010s. More and more companies are talking about it, and many are using computing power in routine decision-making (see e.g. Autor et al., 2003). However, only a few are actually using its capabilities in non-routine decision-making. The potential benefits of AI, if it could be used in decision-making to improve decisions, are invaluable.

Some decision-making processes are so complex that incorporating AI is easier said than done. Decisions of this kind often require management accounting (MA) information. I argue that in order to accelerate the adoption rate of AI, first complicated decision-making processes need to be studied in detail. After that, we are ready to discuss how AI could be implemented. Despite the great opportunities, the combination of decision-making and AI has been neglected among MA researchers, which means that I will have to address this research gap. Several researchers (Rikhardsson and Yigitbasioglu, 2018; Moll and Yigitbasioglu, 2019) have also recently realized the need for studies in this field. Thus, I focus solely on non-routine decisions in this thesis.

1.2 Research questions and methods

As I cannot completely solve the issue in one or even two theses, I have formed three research questions, which I will address in this piece of work:

> *RQ1.* How does management accounting information initiate and influence complex decision-making processes?
>
> *RQ2.* What kinds of artificial intelligence (AI) needs emerge in managerial work?
>
> *RQ3.* What kinds of boundary subjects are expected in decision-making with AI?

The *RQ1* seeks to elaborate the role of management accounting information in complex decisions. This corresponds to my above-mentioned statement on the need for better understanding of complicated decision-making processes. The RQ2 examines a customer perspective of the AI adoption – what kinds of needs the anticipated AI users i.e. decision-makers have? The RQ3 goes even deeper – who are making decisions with AI and are they different in comparison with non-AI decisions? I state that answering these questions will provide first aid to the research gap.

For filling the gap, I chose interpretivist research philosophy and qualitative multiple-case study method. I managed to get 11 interviews in four case companies, which form the data for my cross-case analyses. The cases cover production forecast, sales targeting, productivity investment and target setting decisions. The structure of this thesis is as follow: in the second chapter, I will conduct a systematic literature review. The third chapter is about the methodology in detail. In the fourth chapter, I will go through the empirical data thoroughly and in the fifth chapter, I will synthesize the empirical findings into propositions and hypotheses and discuss their relation to literature. Finally, in the sixth chapter, I conclude the thesis and suggest future research topics. Now turning to the second chapter, literature review.

2. LITERATURE REVIEW

2.1 Key concepts

Before jumping into the literature review, I want to clarify some terminology used in this thesis. Probably the most ambiguous terms in management accounting (MA) literature are related to the information it constantly uses, modifies and produces. It was an important decision, whether to use accounting information, financial information, MA information or some other term in this thesis. The case companies (introduced in Chapter 3) utilize substantial amounts of non-monetary information, for example production volume (pcs) or sales proportion of product A to product B (percentage). Thus, using financial or accounting information would imply that the information is always monetary. Therefore, I decided to use *MA information*, as in my definition it is information used by management accountants, which includes both financial and non-financial information.

Another key concept is to define, what *artificial intelligence* (*AI*) is. As the second and third research question seek to elaborate on the discussions we had with the informants (introduced in Chapter 3), we let them decide and consider what AI is. If an informant used other AI related terms such as machine learning (ML) or neural network (NN), I used the exact terms in the data analysis. In the literature review, researchers have used several related terms such as accounting information system (AIS), management control system (MCS), business intelligence and analytics (BI&A) and big data (BD) just to name a few. All of these may contain some AI functionalities. Moll and Yigitbasioglu (2019) support the idea as they note that AI may overlay BD, cloud and blockchain technologies. I decided to use the original terms in the literature review and therefore keep the unique ideas of the authors as visible as possible. Hence, the reader should keep in mind that the terms overlap each other.

The *RQ1* incorporates the term *complex decision*. Complexity is an arguable expression due to its subjective nature. In my perspective, a complex decision has the following characteristics: 1) it is non-routine; 2) the decision-making process is not linear; 3) the outcome is unclear; 4) there are many uncertainties and 5) the business impact is high. For example, deciding where a coffee machine should be in a factory is not a complex decision (although it was a matter of life and death in one company not analyzed in this thesis), but deciding where the whole factory should be is definitely a complex decision.

An *actor* could be defined in many ways. In Actor-Network Theory (ANT), of which development started in late 1970s mainly by Bruno Latour, Michel Callon, John Law (Lukka and Vinnari, 2014), an actor is *'any thing* that does modify a state of affairs by making a difference' (Latour 2005, p. 71). However, in this thesis an actor is a person, who is directly linked to decision by either being a decision-maker or by affecting decision-making. My definition also follows the idea of pragmatic constructivism, in which undertaking actions require integration of facts, possibilities, values and communication (Nørreklit et al., 2010). Next, I will shortly explain how the literature review was conducted.

2.2 Literature review methodology

The systematic literature review consists of four topics: 1) MA information in decision-making 2) boundary objects, boundary subjects and boundary work 3) knowledge integration and 4) MA information and AI – What is expected? The first topic is related to RQ1, the second to RQ3, the third to RQ1 and RQ3, and the fourth to RQ2. The research questions and their corresponding literature review chapters are illustrated in *Table 1*.

Table 1. *Research questions and their corresponding literature review sections.*

	Research Question	**Corresponding sections**
RQ1.	How does management accounting information initiate and influence complex decision-making processes?	2.3, 2.5
RQ2.	What kinds of artificial intelligence (AI) needs emerge in managerial work?	2.6
RQ3.	What kinds of boundary subjects are expected in decision-making with AI?	2.4, 2.5

I used Scopus for searching articles related to these topics. Finding the right search criteria took a few rounds of trial and error, which I did not document. The resulting criteria of this process are shown in *Table 2*.

Table 2. *Key literature review search criteria.*

Search terms	Subject area	Year	Results
("management accounting" OR "management control" OR "costing" OR "cost management" OR "AIS" OR "MCS") AND ("artificial intelligence" OR "machine learning" OR "neural network")	Business, management and accounting	2010–2019	304
"management accounting" AND ("AI" OR "machine learning")	All	All	20
"boundary subject"	Social sciences; Business, management and accounting; Decision sciences; Economics, econometrics and finance	All	18
("boundary object" OR "boundary subject") AND "management accounting"	All	All	7
"knowledge integration" AND "management accounting"	All	All	3

After finding the results of the searches, I read the titles and decided whether it was relevant to some of the above-mentioned four topics. Next, I checked from the Finnish Publication Forum (JUFO) that the level of the publication is at least one, which simply mean that it is peer-reviewed and has an expert editorial board. If the paper succeeded on the previous tests, I read the abstract and decided if it was still relevant. If the answer was yes, I read at least conclusions and usually many other parts of it and wrote about it to the literature review if I thought it was interesting. In addition to the direct search method, I used snowballing technique. Searching for articles that have cited especially Hall (2010); Quattrone (2016); Wouters, and Roijmans (2011) proved to be an effective way of finding relevant studies. Therefore, this literature review contains subjective elements and it is not intended to provide an objective and perfect view. However, I read 119 papers and this thesis has 86 references, which should cover the topics to some extent. Turning now to the first part of the literature review, which covers the relationship between MA information and decision-making.

2.3 MA information in decision-making

In this section, I will analyze the literature of management accounting (MA) information in decision-making from two perspectives: the roles and limitations of MA information. This lays the grounding for the whole thesis, as I seek to elaborate the connection between MA information, decision-making and AI.

2.3.1 Roles of MA information

MA information has several different roles (see e.g. Burchell et al., 1980; Tiitola et al., 2019; Mouritsen and Kreiner, 2016). One of the MA literature classics, Burchell et al. (1980), identified the following four roles of accounting: answer machine, learning machine, ammunition machine and rationalization machine. As an answer machine, the MA information gives rational answers, which drives the organization towards making rational decisions. Learning machine means not only getting rational answers, but the actors also learn something else than the answer itself e.g. gain better understanding of the decision context. When the information is used to promote actors' own interests i.e. politics, its role is ammunition machine. If the decision has already been made either formally or informally, and the goal of the information is to legitimize the decision, it is seen as a rationalization machine. The roles are presented on *Figure 1*, in which the horizontal axis on the graph shows the uncertainty of objectives and the vertical axis the uncertainty of cause and effect.

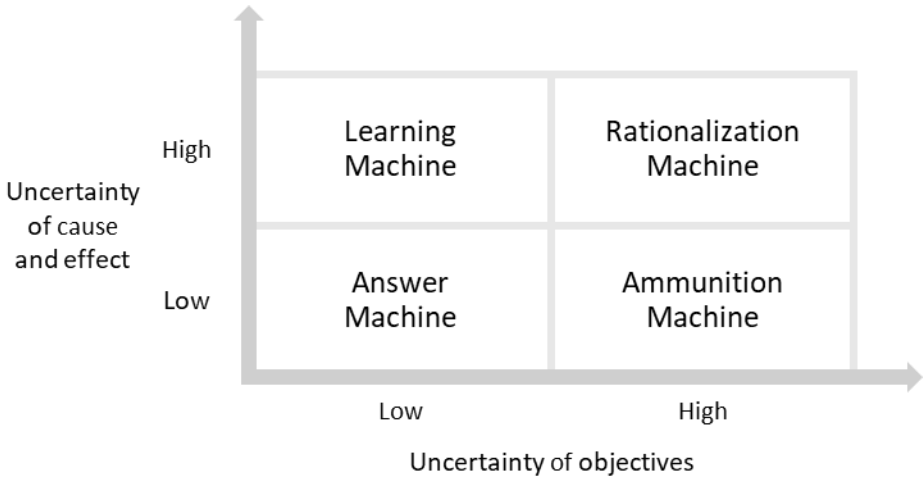

Figure 1. *The roles of MA information in decision-making. Adapted from Burchell et al. (1980).*

Tiitola et al. (2019) recently provided empirical evidence on these roles, as they seem to exist in complex non-routine decisions. Mouritsen and Kreiner (2016, p.29) argue that accounting has a role of promise as a decision is a promise for action: *'It is a commitment to taking the decision seriously and not only literally, and this requires more investment.'* However, they outline that it does not mean promising results in any way. Laine et al. (2012) analyze MA roles in servitization with three perspectives: justification, defining and controlling. In their terminology, the first answers to the question *'Why do we desire servitization?'* the second *'What does servitization mean to us?'* and the third *'How does servitization proceed/affect us?'* In the case of Ahrens (2018), cost management had an *'anchor'* role in a retail bank, which means it controlled other functions e.g. service division and HR. However, these 'subsidiary practices' opposed the controlling mechanism, and work process structuring was achieved not only with encouragement, but also with threats. Accounting has also a role as enabling, and sometimes disabling, compromises in decision-making (Chenhall et al., 2013). According to Cools et al. (2017), MA information, more specifically budgeting, seems to has a role as a creativity stimulator when used either diagnostically (evaluating performance and holding people accountable, Abernethy and Brownell, 1999) or interactively (continuous knowledge transfer between top and middle managers, Abernethy and Brownell, 1999).

Hall (2010) points out that accounting information is just one information source among others for a manager and argues that the information should be analyzed in relation to other types of information such as market data or informal reports. The study underlines that accounting information may initiate verbal conversations about problems and it is used also for creating knowledge about the working environment. Nielsen et al. (2015) found out in their first outsourcing case study that accounting department was not directly involved in the decision-making. The roles of accountants were to provide requested information to the decision-makers and to maintain the accounting information system. The information set supporting decision-making consisted of not just MA information (cost and revenue impact) but also quality, competence, customer service, customer retention and risk analyses. These findings confirm Hall's (2010) conclusion on the relative importance of MA information. In the second outsourcing case of Nielsen et al. (2015), MA information had the ability of veto a project if the target costs, profit margins and rates of returns do not meet the requirements. Accountants are actively involved in the NPD (New Product Development) process and MA information is used in retrospective performance reviews. Managerial bonus system is based on meeting financial targets. Thus, MA information had a key role in this second case. In both cases, MA information is important for the strategy implementation, the first one is more analytical and the latter more actor based.

In the case of Cullen et al. (2013), MA information had a noteworthy impact on the operations management of a retail company's logistics. According to their interpretation, a key success factor was that management accountants and the Head of Quality & Cost Reduction engaged widely within the company, which gave them credibility and made operational changes possible.

Busco and Quattrone (2015) draw our attention to four new viewpoints of the classical Balanced Scorecard (BSC) framework. They see it as a visual performable space, method of ordering and innovation, means of interrogation and mediation, and motivating ritual. Busco et al. (2015) elaborate the viewpoints with their case studies. In one case, visualizations of Six-Sigma helped people to connect customer voice to processes of the organization. In the same case, the Define, Measure, Analyze, Improve and Control (DMAIC) framework steered the process re-engineering without constraining the innovativeness. The other case, in which two new business units (BUs), an end-to-end budget and profit and loss statement (P&L) were created, relied on both informal and formal media in order to make them work. Last, in both cases the above-mention MA information enabled discussions and disagreements, in other words, worked as a motivating ritual.

2.3.2 Limitations of MA information

There are several different limitations in utilizing MA information in decision-making. Saukkonen et al. (2018) suggest in their case study that (1) managers lack skills in using MA information, (2) they may not reflect taken-for-granted assumptions, (3) the needs regarding timing, scope and content may differ from manager to manager, and (4) the decision-making process may ignore some viewpoints. The first suggestion is in line with Sutton et al. (2016), who wonder if accounting decision-makers are able to make good use of different machine learning techniques. In addition, Saukkonen et al. (2018) found that fixed decision-making cycles of an enterprise delivery company decreased flexibility and operational efficiency.

Rowe et al. (2012) maintain that MA information users are usually having doubts about the quality of the information and the interviewees may intentionally bias the ‘soft information’. They define soft information as open to debate, and it requires a social hardening process so actors can go along with it and start using it. Rowe et al. (2012) identified four types of hardening games from literature: faith game (faith in experts, Briers and Chua, 2001), power and politics game (see ammunition machine in Burchell et al., 1980), practical arguments game (practical reasoning, Jönsson and Lukka, 2006) and statistics game (independent verification through statistical means, Christensen and Skærbæk, 2010).

In their two cases, Christensen and Skærbæk (2010) found that hardening, or in their terminology purification, is crucial for change in accounting practices, and consultants may endorse the hardening process. However, Rowe et al. (2012) argue, based on their case, that hardening is successful when practical argument game is in place. Their reasoning is based on the interpretations that the players think it is the most legitimate and democratic type of the games and it is played without technical language, which makes participation easier.

Englund and Gerdin (2015) propose that actors may need to utilize their operational knowledge for understanding accounting information. Busco and Quattrone's (2018) case study in an Italian fashion company revealed that there are challenges in combining data analyses from sales and marketing with the feelings and ideas of individual stylists, when they are having a meeting about a new collection. In the prototyping phase, there are many discussions on finding a balance between designs, costs, producibility, ethical matters and promises to sales agents and clients. However, only products, that meet or get close to certain contribution margin, will undoubtedly be commercialized. Similarly, in Goretzki and Messner's (2016) empirical findings it was crucial for planning meetings' functionality to find 'a common understanding between sales and operations managers'. Interestingly, as the operations manager did not know the background of the forecasts, he depended on other information sources (e.g. historical sales, budget and order book) in order to participate in statistical reasoning. Moreover, they found that the role of MA information was not to just answer an information need, but also to create ambiguity, which directed the conversation towards collective sense making.

However, Wouters and Roijmans (2011) claim that joint ownership of an accounting experimentation helps with integrating different viewpoints as the participants need to reach a common goal. According to Thomas (2016), communicating the high-level goal of better decision-making and giving feedback on short-run success in management accounting system (MAS) revision motivates actors to continue their efforts. Notwithstanding with the benefits of the feedback, the reporting of short-run success may have a demotivating effect on the actors in further MAS development, if the high-level goal is not known.

In NPD context, Laine et al. (2016a) say the potential financial (or non-financial) impacts cannot be forecasted or managed by just rational means. They base their reasoning on several uncertainties, which hinder the outcome. Nevertheless, they also state uncertainties may initiate collective sense making, which may improve the outcome of the project. Jørgensen and Messner (2009) found in their NPD case study that enabling control system helps employees to adjust it when needed. Nevertheless, they would have needed support from top management in a radical re-design effort.

2.3.3 Summary

The interest in the roles of MA information and its limitations among researchers seem to be relatively low. There are not many new roles introduced after the classical Burchell et al. (1980) suggesting the roles of ammunition, learning, rationalization and answer machines. However, Mouritsen and Kreiner (2016, p.29) states that there is also a role of promise. Research and discussion on the limitations of MA information seems to have gained some momentum in the 2010s (cf. Saukkonen et al., 2018).

Most of the introduced case studies do not elaborate on how actors actually use MA information in detail. The studied cases are also typically rather unambiguous, which leaves room for empirical research on ambiguous and complex decisions. Next, I will introduce a few papers on boundary objects, boundary subjects and boundary work.

2.4 Boundary objects, boundary subjects and boundary work

Several studies, for instance Briers and Chua (2001), Huzzard et al. (2010) and Laine et al. (2016), have been carried out on boundary objects and/or boundary subjects. The concepts are essential for understanding decision-making as an interpersonal phenomenon. Next, I will briefly introduce those.

2.4.1 Boundary objects

On the one hand, the idea behind boundary objects is that they hold different actors together (Briers and Chua, 2001). On the other hand, they are a language used for communicating knowledge of different individuals (Carlile, 2002). Star and Griesemer (Star, 1989; Star and Griesemer, 1989) originally introduced the concept of boundary objects and identified repositories, ideal types, coincident boundaries and standardized forms as examples. Briers and Chua (2001) confirmed not only the examples, but also visionary objects, as boundary objects in their case study. However, Carlile (2002) found that not all the used objects are boundary objects and their function depend on the context. He also proposes that an effective boundary object enables a process, which allows actors to learn about their differences and to transfer their knowledge. After roughly two decades, Star (2010) stated that many people have asked her ‘what is not a boundary object’. Instead of giving a clear answer, she encourages the reader to think about scale and scope; in some context, a single word can be a boundary object, but usually the concept is most beneficial at the organizational level. Empirical evidence has pointed out that enterprise resource planning systems (ERP) can be important boundary objects in companies (Cullen et al., 2013). In the cases of Chenhall and Euske (2007), Activity-Based Cost Management (ABCM) systems sought to integrate knowledge as boundary objects. Even non-traditional information sources, such as social media platforms, may become boundary objects for management accountants (Arnaboldi et al., 2017).

2.4.2 Boundary subjects and boundary work

The study of Huzzard et al. (2010) was the first step towards enhancing our understanding of boundary subjects. They contended that individuals can be boundary objects, but they cannot be politically neutral, which would make it beneficial to understand them as *boundary subjects* rather than boundary objects. Windeck et al. (2015) argue that the business partner role of management accountants is a boundary object, but they failed to provide adequate proof of this finding. If management accountants are becoming business partners (cf. Goretzki et al., 2013; Windeck et al., 2015), I state they are becoming boundary subjects (as accountants are supposedly humans) rather than objects. Azambuja and Islam (2019) share this viewpoint in their study concerned with middle managers in an auditing firm. In healthcare, Bishop and Waring (2019) argue that patients differ from other boundary objects as they have the possibility to become boundary subjects since they should have an influence on their own care.

An actor, who is not a decision-maker, may also have an impact on decisions. Hall et al. (2015) studied risk managers' influence methods in two banks and found two key mechanisms. First, the risk managers developed personal connections with other managers by providing analysis and interpretation of "guarded tools" during decision-making. Second, the risk managers developed, operated and edited these tools, which included their and others' expertise. These tools worked as boundary objects enabling knowledge integration between risk managers and other managers.

Laine et al. (2016b) showed us that utilizing boundary subjects in gathering and conjoining accounting facts from different actors is useful. Furthermore, they also underline that boundary objects, for example accounting prototypes, may support discussions between decision-makers and help them to develop a shared vision.

In addition to the boundary object and boundary subject discussion, Azambuja and Islam (2019) investigated middle managers' *boundary work* in their recently published ethnographic study. They found that their interviewees think being good at boundary work requires the ability to adapt to several roles many times a day and therefore enabling collaboration between functional and hierarchical boundaries. This led the middle managers to have not just positive experiences like expertise, autonomy, empowerment and reflexivity, but also negative ones such as fatigue, lack of self-determination and detachment from their profession and coworkers.

2.4.3 Summary

Boundary objects and boundary subjects offer an intriguing snapshot for management accountants to the world of social sciences. It is essential to understand that boundary objects (e.g. budgets) also serve other purposes than being just answer machines (Burchell et al. 1980). For example, another purpose may be that the object is a language between actors.

The discussion among researchers concerning these topics is fragmented. For example, boundary object is not a widely applied term among MA researchers, not to mention boundary subject, which is replaceable with other terms such as actor or decision-maker. I used only papers using the exact terms, which limits the results. Next, I will introduce some knowledge integration papers, which enhance our understanding on how boundary subjects i.e. actors integrate their knowledge.

2.5 Knowledge integration

Integrating knowledge between accountants and operations managers is hard (Wouters and Roijmans, 2011). Next, I present some studies from 2010s trying to address the difficulties of knowledge integration in management accounting and decision-making contexts.

2.5.1 Knowledge integration and its limitations

First, Wouters and Roijmans (2011) draw our focus on the topic by studying knowledge integration in a development process of an enabling performance measurement system (PMS). They found in the action research that accounting experiments (incomplete spreadsheets) got actors from different functions to ask questions, which were then answered by others, thus knowledge got integrated. In addition, they argue that utilizing real data and joint ownership, i.e. shared goal between accountants and non-accountants, with the experiments are assets in knowledge integration.

In the case company of Giovannoni and Maraghini (2013), managers from different functions are discussing and solving problems together on a weekly basis in a performance review meeting. This social interaction has advanced knowledge integration in the firm operating in highly unpredictable fashion industry. For example, sharing knowledge between production and stylists have enabled the latter to understand how creative choices may affect production efficiency. According to Coyte (2019), the enabling use of management control systems (MCS) created valuable local knowledge and relationships in their case company. The MCS built understanding between financial metrics and operational decisions among operative non-management employees.

A study of a creation of a new bioscience network by Spanò et al. (2017) suggests that the acceptance of change and willingness to improve a new management accounting system (MAS) increased among all the informants when they understood the following three advantages. First, new relationships were created beyond the network, which enhanced knowledge sharing. Second, utilizing MAS helped with integrating knowledge and finding best practices within new network-level projects. Third, the inevitable cooperation within the new network allowed the informants to learn new knowledge, which they can take back to their own organizations.

Combining different viewpoints of different actors requires compromises (Chenhall et al., 2013; Goretzki et al., 2018). Chenhall et al. (2013) studied how accounting practices affect compromises on developing new PMS and found that imperfection of the accounting object enabled discussions, and therefore continuous adjustments. In addition, concurrent visibility of actors' evaluation principles seems beneficial for the development process. They also revealed two types of criticism: one concerned the idea of ranking operations in different locations based on their performance, which led to a new practice combining the 'competition' and 'learning' perspectives. The other one debated on the lack of consistency in the object. This, however, was not constructive but hindered the development process as it took up meeting time with pointless technical arguments. Goretzki et al. (2018) elaborates the idea of compromises by demonstrating how vernacular accounting systems (VAS), such as Excel files, can help with a development of an enabling global accounting system. The results show that VAS helped actors to communicate and negotiate local knowledge to be included in the new system. The VAS also ensured that local actors could test the new system against the old local ones.

In terms of time dimension, Giovannoni and Quarchioni (2019) found that in one case, an imperfect PMS empowered managers to forget and forgive past decisions, and to create new knowledge and projects. Wouters and Kirchberger (2015) state that in the development of customer value proposition, knowledge transformation may be necessary. Value proposition has not only the name of the value element (e.g. reduced maintenance costs) but also the measurement (1.5 hours or €150 per week). In their reasoning, utilizing only the first may not reveal misunderstandings, which require knowledge transformation in order to create mutual agreement. The results of Bisbe and Malagueño (2015) state that *'the emphasis companies place on 1) value systems and 2) interactive control systems […] are positively associated with co-ordination and knowledge integration activities in product innovation processes.'* The results were statistically significant.

However, they did not find statistically significant association between diagnostic control systems and co-ordination and knowledge integration.

When it comes to the limitations of knowledge integration, Strathern (2000) draw our attention to the tyranny of transparency: *what does visibility conceal?* Quattrone (2016) continues the discussion by outlining that making some financial transactions more transparent actually increases the opacity as it hides the rest of the transactions. If transparency is achieved through informal knowledge sharing as Jørgensen and Messner (2009) suggest in their NPD case, it is hard to imagine how there could be tyranny of transparency in this kind of knowledge integration method. However, I think the tyranny of transparency can be utilized at least as a method of ammunition machine from Burchell et al. (1980), but also accidentally if managers blindly focus on just the chosen metrics.

2.5.2 Summary

I have outlined in the previous sections how management accounting (MA) information is used in decision-making and why boundary objects (e.g. budget) and boundary subjects (actors) are important. In this section, I have discussed how these are working together i.e. how knowledge is integrated. To mention two key findings, firstly Wouters and Roijmans (2011) found that incomplete boundary objects are important as they raise questions and induce discussions among boundary subjects. Secondly, Quattrone (2016) argues that making some financial transactions visible may increase the opacity of others. Now that I have covered the essential backgrounds for decision-making with MA information, I will go through recent literature on the symbiosis of MA information and artificial intelligence (AI).

2.6 MA information and AI – What is expected?

Recently, there has been increasing momentum among research to address the threats and opportunities of AI. Rikhardsson and Yigitbasioglu (2018) reviewed over 60 high quality studies concerning MA and BI&A (business intelligence and analytics). They argue that there are relatively low number of papers paying particular attention to applications in this field and the interest in creating new knowledge in MA tasks with analytics seems to be limited among MA researchers. An older paper by Granlund (2011) suggests that MA researchers should deepen the role of IT in their studies and to not to take it for granted. Next, I will introduce you to some recent papers on MA information and AI. This section will provide groundings for the upcoming empirical chapters.

2.6.1 Practical cases concerning MA information and AI

Loyer et al. (2016) compared five machine learning methods on predicting manufacturing costs of jet engine components in the early design stage. Best two methods, gradient boosted trees ($R^2 = 0.96$) and support vector regression ($R^2 = 0.93$) proved to be very accurate. Thus, they argue that cost predictions could be part of decision systems and at some point, part of CAD/CAM tools. The paper of Kumar et al. (2017) shows how artificial immune system and particle swarm optimization algorithms can be used in reverse logistics to optimize costs, profits and vehicle routes. The results implicate that artificial immune system gave better results. Camacho-Miñano et al. (2015) utilized two different AI methodologies, rough set theory (RS) and PART algorithm, on 1,387 bankrupt Spanish companies and found that *'sector, size, number of shareholdings, ROA, and liquidity could explain the bankruptcy process outcome and also predict the process for still-healthy firms.'* In supply chain risk management literature, most of the AI studies are concerned with designing and evaluating a mathematical model, which leaves room for papers studying their practicalities (Baryannis et al., 2019).

Artificial intelligence and MA have gained momentum together among researchers studying the construction industry. Petroutsatou et al. (2012) studied how neural networks (NN) could predict road tunnel costs based on data of 22 tunnels totaling 46 km. The results show that the overall accuracy of their multiple regression analysis was 90.6% and of neural network 95.35%. Thus, they argue that AI has practical value in cost estimation of construction projects and probably also in other industries. Alqahtani and Whyte (2013) used two NN methods, back-propagation with MATLAB and spreadsheet optimization using Excel, to estimate total running costs of 20 building projects. They reached the accuracy of 1 % with Excel solver and 2 % with backpropagation. Shehab and Farooq (2013) developed a NN to predict the construction cost of water and sewer rehabilitation projects. The model was based on 54 projects in San Diego, California, USA, and it reached the accuracy of $R^2 = 0.8959$ when tested with another set of projects. Cheng et al. (2015) developed an evolutionary fuzzy support vector machines inference model for predicting change order productivity losses in construction projects. The model reached the average absolute error of 6.24%, thus making it easier for project managers to manage the losses.

Despite the limited number of practical studies of MA information and AI, there is a vast amount of literature on accounting information systems (AIS) (see e.g. Grabski et al., 2011; Ruggeri and Rizza, 2018; Wiersma 2009). An AIS innovation may become a boundary object as Ruggeri and Rizza (2018) found out in their longitudinal case study; a reengineering process of the supplier selection helped collaboration between actors.

They also suggest that a successful AIS innovation requires aligning the interests of all the participants. Ismail and King (2005) revealed in their survey on Malesian SMEs that many companies are short of AIS processing capacity compared to their AIS requirements. The combination of these, in their terms AIS alignment, was found to have a positive correlation with firm performance. Despite being rather old study, the results may be transferrable to MA and AI context.

There amount of practical studies of AI solutions is very limited. The found use cases, especially in the construction industry (cf. Petroutsatou et al., 2012; Shehab and Farooq, 2013) provide promising results. I would like to see much more similar empirical studies in the future, as it would enhance our understanding on combining management accounting and AI. Next, I will move on to the processes of utilizing AI in decision-making.

2.6.2 AI process in decision-making

Arnaboldi (2018) introduced us to two big data (BD) processes, filtering and framing. The filtering means that a data scientist is constantly making decisions on which data is included and which is not. The framing process, however, is about giving the data a relevant context and then communicating the data in a way it would become valuable in the decision-making. Arnaboldi (2018) argues that these processes flow through a BD chain, which has five phases that illustrates the progress from data acquisition to the visualization of the results. First, the data needs be acquired, cleaned and recorded. Second, it is analyzed with clustering and annotation. Third, the data is integrated and fused. Fourth, it is modelled and analyzed and finally fifth, it is visualized. *Figure 2* shows the BD chain.

Figure 2. *Big data chain. Adapted from Arnaboldi (2018).*

Next, Arnaboldi (2018) combines her BD chain and the two processes into a single framework, which has the decision-makers in the center. Thus, the illustration highlights the role of decision-makers and puts the value of BD for decision-making in a social context with social, economic and environmental trends and stakeholders. The new framework of BD in decision-making is represented in *Figure 3*.

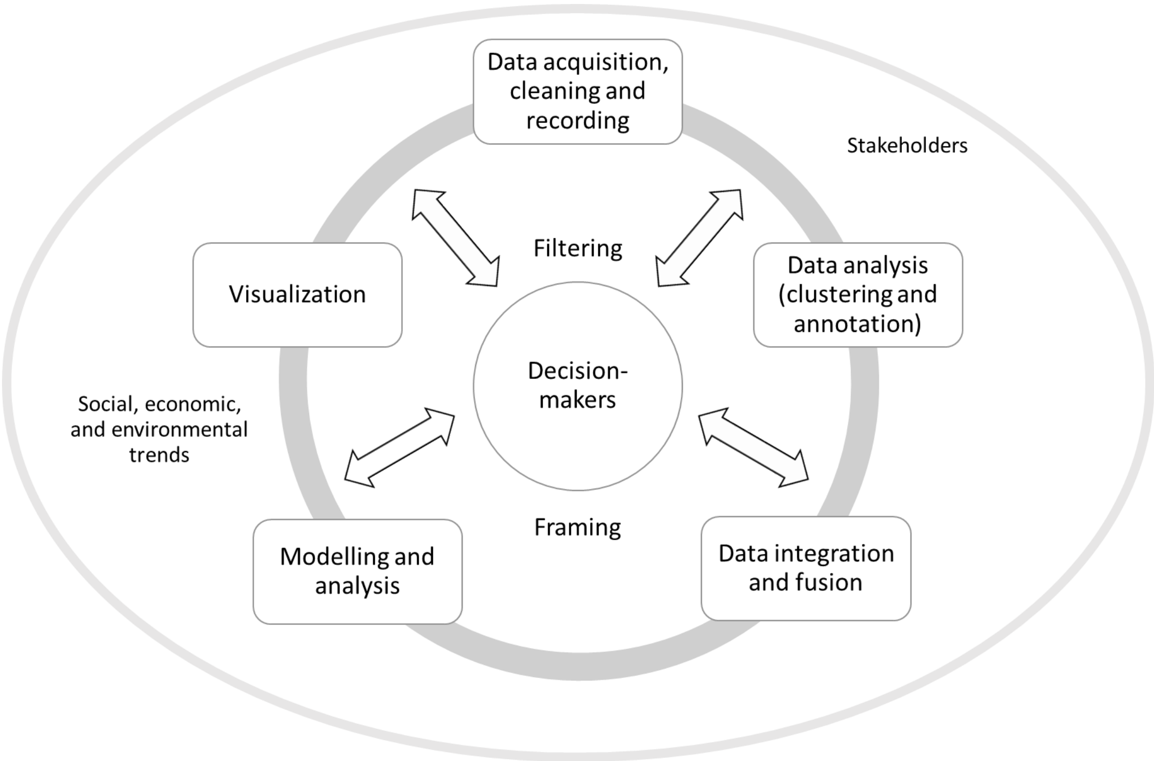

Figure 3. *Big data process in decision-making. Adapted from Arnaboldi (2018).*

The BD chain of Arnaboldi (2018) is essentially same as the BD phases introduced by Gärtner and Hiebl (2017), who divide it to three phases: 1) data generation and storage, 2) data processing, verification and analysis, and 3) reporting and decision support. At the organizational level, Kolbjørnsrud et al. (2017) suggest three steps to success: 1) start exploring AI now – together 2) keep track of AI use 3) craft new recruitment and training strategies.

Shrestha et al. (2019) introduced us to five conditions differs between human and AI decision-making. First, the specificity of the decision must be well defined with AI as humans can cope with more loose situations. Second, the decision-making process of AI may be hard to interpret compared to the human version. Third, humans cannot evaluate as large set of alternatives as AI. Fourth, AI is much faster and it does not make trade-offs between speed and accuracy as with humans. Fifth, the decisions made by humans incorporate many individual related factors such as attention, experience and emotions, which are lacking with AI. The five conditions are expressed in *Table 3.*

Table 3. *AI- and human-based decision-making. Adapted from Shrestha et al. (2019).*

Decision-making Conditions	**AI-based decision-making**	**Human decision-making**
Specificity of the decision search space	Requires a well-specified decision with specific objective functions	Works in a loosely defined decision search space
Interpretability of the decision-making process and outcome	The decision process may be difficult to interpret	Decisions are well explainable and interpretable
Size of the alternative set	Accommodates large alternative sets	Limited capacity to evaluate a large alternative set
Decision-making speed	Fast, limited trade-off between speed and accuracy	Slow, high trade-of between speed and accuracy
Replicability of outcomes	Decision-making process and outcomes are highly replicable due to a standard process	Replicability incorporates inter- and intra-individual factors such as differences in experience and emotional state of the decision-maker

I argue based on this section that incorporating AI in decision-making requires a clear process. Decision-making with AI seems to have also differences when compared to utilizing just humans. Next, I will move on to the challenges that come with AI.

2.6.3 Challenges with AI

In addition to her above-mentioned new framework, Arnaboldi (2018) reaches the conclusion that there are two risky behaviors in decision-making with BD: blind faith and reluctance. The first indicates too high expectations of BD and the second means resistance to BD if the decision-maker does not understand all the details of it.

The constantly increasing digitalization of work brings also challenges. It reduces the amount of communication between people, which is a problem when the system does not work, and no one knows what to do (Payne, 2014). When it comes to managers' trust in advice from AI, Kolbjørnsrud et al. (2017) found that only 18 % of the managers of developed countries strongly agreed to trust the information while in emerging countries (including China) it was 46 %. They also argue that *'Executives cannot assume that mid- and lower-level managers will share their appreciation for AI.'* On the other hand, Sutton et al. (2016) bring into question whether solutions with high predictability but low explicability lead up to increased or decreased acceptance and dependency on AI. Quattrone (2016) claims that digitalization is an opportunity to improve information judgement before using it, although his guess is that decision makers will make wrong decisions much more quickly with the help of big data. In addition, new governance activities may be required with AI as it would be too easy to put the blame of bad decisions on the technology (Moll and Yigitbasioglu, 2019). Now that I have gone through past and present perspectives of AI, I will continue the discussion with a future perspective.

2.6.4 Future perspective of Accounting and AI

AI and other technologies will inevitably change the role of management accountants in the future. Moll and Yigitbasioglu (2019) state that accountants will be still needed for some traditional processes e.g. performance management. They also argue it is a duty of accountants to challenge the results that AI brings on the table and to take caution when someone uses the system as a black box without proper understanding. Richins et al. (2017) state that as many current tasks of accountants will be automated, new opportunities of problem-driven analyses emerge with structured and unstructured data. They draw our attention to four skillsets in developing accountants to these new roles. First, accounting skills should be complemented with strategy and business models of the particular firm. Second, accountants should have sufficient business analytics skills from extracting the data to communicating the results. Third, they should be able to work with big data tools and both structured and unstructured data. Fourth, accountants should have basic understanding of programming.

Some institutional work, including (re-)constructing role identities, legitimizing the new role and linking the intra-organizational level with an institutional environment, may be required when the role change of management accountants is put into action (Goretzki et al., 2013). Bhimani and Willcocks (2014) argue that accounting functions of many companies are going through great changes since data information and technology are improving, which creates more possibilities for financial information as the roles of it are fundamentally changing. They note that some accounting executives are coming out of their usual job to guide operational decisions at least in enterprises, thus analysis is coming closer to the execution with the help of big data (BD) technologies. Parry et al. (2016) underline positive impacts of AI on decision-making as it may hinder the agency problem and de-individualize decision-making in organizations.

2.6.5 Summary

In this section, I have gone through practical cases, processes, challenges and future perspectives of AI, decision-making and management accounting (MA). The amount of practical AI cases in the MA field is very limited, but there are some interesting results especially in the construction industry predicting construction costs (cf. Petroutsatou et al., 2012; Shehab and Farooq, 2013). I argue that decision-making with AI requires a clear process such as the one introduced by Arnaboldi (2018). The tasks of the accounting function are most likely going through a change, which will also bring new data-related opportunities for accountants (Richins et al., 2017). In the next section, I summarize the whole literature review before heading to the empirical parts of this thesis.

2.7 Summary of the literature review

To sum up this literature review chapter, I have shown how management accounting (MA) information is used in decision-making and why boundary objects (e.g. budget) and boundary subjects (actors) are important. Next, I elaborate how these are working together i.e. how knowledge is integrated and how artificial intelligence (AI) is reshaping these. The review is based on approximately 80 papers.

First, the interest in the roles of MA information and its limitations among researchers seem to be relatively low. There are not many new roles introduced after the classical Burchell et al. (1980) suggesting the roles of ammunition, learning, rationalization and answer machines. Mouritsen and Kreiner (2016, p.29) states that there is also a role of promise in addition to the work of Burchell et al. (1980). However, research and discussion on the limitations of MA information seem to have gained some momentum in the 2010s (cf. Saukkonen et al., 2018). Second, boundary objects and boundary subjects offer an intriguing snapshot for management accountants to the world of social sciences. It is essential to understand that boundary objects also serve other purposes than being just answer machines (Burchell et al. 1980). For example, another purpose may be that the object is a language between actors. Third, in knowledge integration discussion, Wouters and Roijmans (2011) found that incomplete boundary objects are important as they raise questions and induce discussions among boundary subjects. In addition, Quattrone (2016) argues that making some financial transactions visible may increase the opacity of others. Fourth, the amount of practical AI cases in the MA field is limited, but there are some interesting results especially in the construction industry predicting construction costs (cf. Petroutsatou et al., 2012; Shehab and Farooq, 2013). I argue that decision-making with AI requires a clear process such as the one introduced by Arnaboldi (2018). The tasks of the accounting function are most likely going through a change, which will also bring new data-related opportunities for accountants (Richins et al., 2017).

To conclude further this chapter, I draw *Figure 4* to illustrate my interpretation on decision-making without AI according to the literature review, the AI (big data) process introduced by Arnaboldi (2018) and an unknown decision-making process when the first two are combined together. Starting from the top of the figure, the decision-making process without AI consists of steps and actors, who are interacting together with knowledge integration. If there are boundaries between the actors, for example, functional boundaries, the actors become boundary subjects and they need to do boundary work. In many cases, there are also boundary objects, e.g. Excel sheets that help the actors to make the required decisions. Here, I argue that AI is a special type of boundary object, which deserves more research in the decision-making and management accounting contexts. Next, *Figure 4* shows the AI process, which is adapted from the big data chain of Arnaboldi (2018). The idea of this chain is to provide an overview of what kinds of steps AI utilization may require and to pinpoint that they differ from traditional decision-making. When these two are combined to a single decision-making process, my literature review raises more questions than gives answers. Only few researchers have addressed how AI should be incorporated into decision-making and management accounting, and the lack of empirical evidence is even greater. Several researchers (Rikhardsson and Yigitbasioglu, 2018; Moll and Yigitbasioglu, 2019) have also realized the need for similar studies. Thus, the bottom element of *Figure 4* consists of mainly question marks to illustrate the research gap.

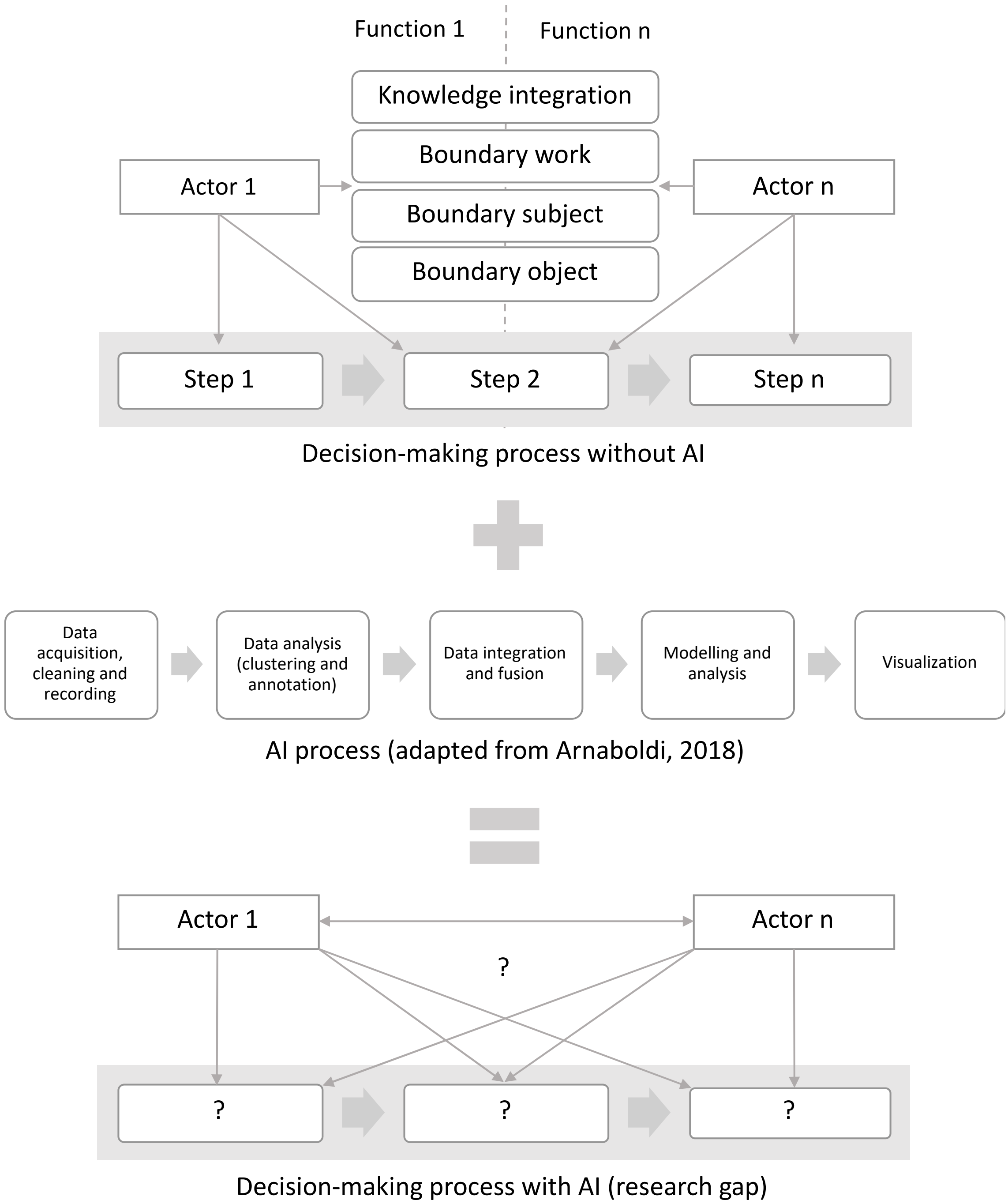

Figure 4. *Decision-making according to the literature review and research gap.*

As *Figure 4* suggests, this specific combination of decision-making with AI has been neglected among researchers. This thesis aims to address this issue. *Figure 5* roughly shows how the research questions relate to the research gap.

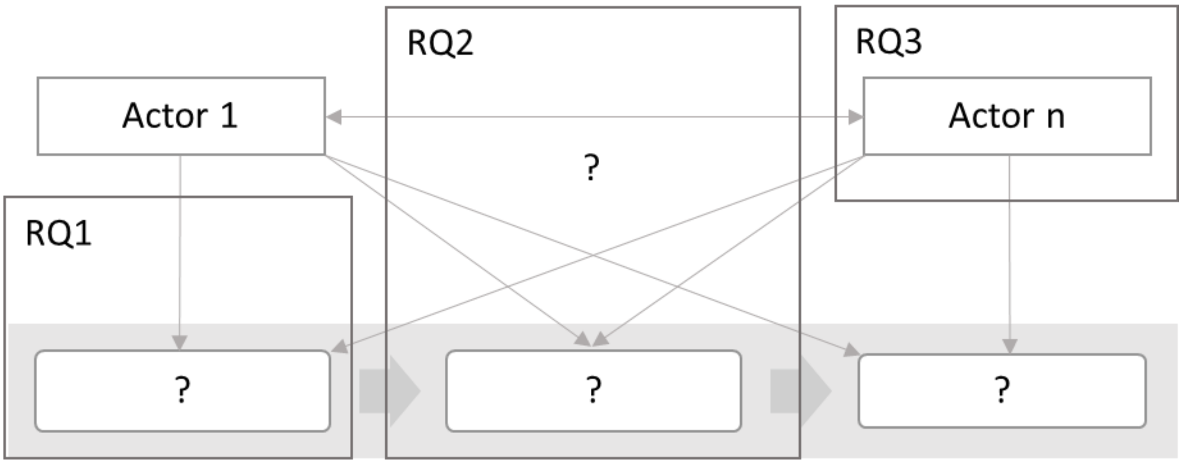

Figure 5. *Decision-making with AI (research gap) and corresponding research questions*

I suggest in *Figure 5* that *RQ1* seeks to reveal, how does management accounting information initiate and influence complex decision-making processes. In *RQ2*, I will study what kinds of artificial intelligence (AI) needs emerge in managerial work. The *RQ3* elaborates expected boundary subjects. Next, I will discuss the methodology of this thesis i.e. how I am going fill the research gap and answer the research questions.

3. METHODOLOGY

I will discuss the research design, data collection and data analysis in this chapter. Silverman and Marvasti (2008, pp. 376) state that the methodology chapter of a dissertation should openly and clearly describe how the research was actually conducted. To build on this, I will discuss the research design of this thesis first.

3.1 Research design

Silverman and Marvasti (2008, pp. 376) argue that in especially empirical dissertations the methodology section is expected to show that the researcher understands the strengths and weaknesses of the strategy, design and methods. This thesis aims to elaborate how complex business decisions are made and how AI will change it. Now I will go through my research design choices based on the model introduced by Saunders et al. (2016, pp. 124). The research design layers, and my choices are shown in *Table 4*.

Table 4. *Research design layers (adapted from Saunders et al., 2016, pp. 124) and my choices*

Layer	My choice
Philosophy	Interpretivism
Approach	Inductive
Strategy	Multiple-case study
Choices	Mono method qualitative
Time horizon	Cross-sectional
Techniques and procedures	Interviews, cross-case analyses

The research philosophy of this thesis is interpretivism. It is a subjectivist viewpoint, which emphasizes the difference between humans and physical phenomena (Saunders et al., 2016, pp. 151). While subjectivity is a weakness, as my own values and beliefs affect the results, it may capture unique circumstances and interactions (Saunders et al., 2016, pp. 140–141). My research approach is inductive, which simply means that I start from the data and generate untested theories (Saunders et al., 2016, pp. 145). Strategy-wise I chose to use multiple-case study as it allows to capture real-life events (Yin, 2003, pp. 2) such as complex human-to-human decision-making processes. However, this decision was more or less made for me by others in the research project, which I discuss further in the next section. I decided to use just one method as it is simple, and it may prevent from under analyzing data. Nevertheless, triangulation may improve reliability when compared to mono method (Saunders et al., 2016, pp. 157–159). My time horizon is cross-sectional, which can be used for describing phenomena or how factors are related (Saunders et al., 2016, pp. 200). This was one of the aims of this thesis – to figure out how complex decisions are made and how MA information initiate and influence them. However, this time horizon does not allow studying change and development as longitudinal horizon would (Saunders et al., 2016, pp. 200). When it comes to techniques and procedures, it was chosen for me by other researchers of the project that I would be conducting interviews. This technique allows both fact- and opinion-based question, but it is a verbal report, which is subject to bias, poor recall and inaccurate articulation (Yin, 2003, pp. 90–92). I chose to use cross-case analyses developed by Bourgeois and Eisenhardt (1988), which helps the researcher to go beyond initial impressions, but may lead to overly complicated theories (Eisenhardt, 1989). The strengths and weaknesses of the choices are illustrated in *Table 5*.

Table 5. *Strengths and weaknesses of my research choices*

My choice	Strengths	Weaknesses	Source
Interpretivism	Captures unique circumstances and interactions	Subjective: researcher's own values and beliefs affect the results	Saunders et al. (2016, pp. 140–141)
Inductive	Takes human perspectives and context of the events into consideration	Risk: lack of emerging data patterns	Saunders et al. (2016, pp. 147–149)
	Allows alternative explanations	Time-consuming, managers are more likely to support deductive approach	Saunders et al. (2016, pp. 147–149)
Multiple-case study	Explanatory studies: good for answering 'how' and 'why' questions	Predictive studies: not good at enumerating 'what' questions	Yin (2003, pp. 5–7)
	Multiple cases improve transferability compared to single case	Requires more resources	Yin (2003, pp. 47, 53)
Mono method qualitative	Simple, may prevent from under analyzing data	Triangulation may improve reliability	Saunders et al. (2016, pp. 157–159)
Cross-sectional	May be used for describing phenomena or how factors are related	Longitudinal study would enable studying change and development	Saunders et al. (2016, pp. 200)
Interviews	Allows both fact- and opinion-based questions	Verbal report: bias, poor recall, inaccurate articulation	Yin (2003, pp. 90–92)
Cross-case analyses	Helps researcher to go beyond initial impressions	May lead to overly complicated theories	Eisenhardt (1989)

Yin (2003, pp. 33–34) state that research design can be judged by four tests: construct validity, internal validity, external validity and reliability. Next I will go through the tests and case study tactics according to Yin (2003, pp. 34) and give my responses to them.

Construct validity tactics are 1) using multiple sources of evidence 2) establishing chain of evidence and 3) having key informants to review draft reports. I used data triangulation as we interviewed several informants on the same decisions. I intended to get original decision meeting memos to improve this, but I realized they do not exist, as the meetings are not usually that formal. In addition, we utilized investigator triangulation as other interviewers checked my work during a research paper writing process and evaluation of this thesis. They also analyzed the data separately and we had some unstructured conversations on the data. Similarly, external sociologists analyzed parts of the data and we discussed the results with them. The structure of this thesis supports the chain of evidence. The empirical findings chapter elaborates the case stories of the informants, which are, together with the literature review, the base for the propositions in the synthesis of findings and discussion chapter. I did not send any draft reports to the key informants, which hinders the construct validity.

The second design test, internal validity, is used for explanatory or causal studies. This thesis is mainly descriptive, so there is no need to address this. I tackled the third test, external validity, using replication logic by making cross-case analyses. However, the results need more testing before they are transferable. The last test, reliability, is somewhat addressed as I followed a relatively clear case study protocol. Nevertheless, the research process was not completely linear (as discussed in the following sections) and it was not well-designed beforehand. Another reliability tactic is to develop a case study database. We stored the interview recordings, transcripts and notes in a folder where everyone in our research group had access. Some of the data was also handed to the previously mentioned sociologists. The research design tests, case study tactics and my responses are shown in *Table 6*.

Table 6. *Research design tests, case study tactics and my responses (adapted from Yin, 2003, pp. 34)*

Test	Case Study Tactic	My responses
Construct validity	Use multiple sources of evidence	I used data triangulation (multiple informants on the same decisions)
	Use multiple sources of evidence	We utilized investigator triangulation (other interviewers checked my work and did their own analyses. External sociologists analyzed parts of the data)
	Establish chain of evidence	I base the synthesis of findings on the empirical findings chapter, which tells the case stories
	Have key informants review draft report	I did not do this. No excuses.
Internal validity	Several	This is mostly a descriptive study, so internal validity is not relevant
External validity	Use replication logic in multiple-case studies	Replication logic is used as I made cross-case analyses. However, the results need more testing before they are transferable
Reliability	Use case study protocol	A relatively clear protocol was used, although it was not well structured beforehand
	Develop case study database	Members of our research group have access to the case study database

Lukka and Modell (2010) state that there are problems in validating interpretative management accounting research. Nevertheless, they point out that it creates rich emic descriptions with etic parts for creating explanations. To further judge the research design, I would like to add that quantitative methods should have been used for RQ2 and RQ3 as they are ‘what’ questions. Yin (2003, pp. 6) suggests that this type of questions favor survey and archival strategies. Alternatively, the research questions should have been changed. In addition, mixing the chosen case-study strategy with action or interventionist research methods would have probably provided results that are more comprehensive. That kind of research design could have partially captured informal communication, which happens during the decision-making processes. This thesis relied only on interviews, which could have been supplemented by direct observation. However, it would have imposed a risk of being an over-complicated research design. Despite the challenges and problems in my research design, Granlund (2011) states that there is a need in AIS research for cross-sectional studies in *‘establishing a wider picture of current practices and trends of development’*. In addition, Korica et al. (2017) specifically called for elaboration on managerial work in practice with qualitative methods.

3.2 Data collection

I wrote this thesis in a research project at Tampere University. As I joined the project during its early stage in January 2019, it had ten committed companies that would provide the project some resources. Four of these companies have a major role with extensive resource commitment and we work with them closely over the two-year period to solve their problems. The rest of the firms, six in total, had approved that we can conduct interviews within their organizations on a significant business decision-making case. The data of this thesis is from four out of those six companies. One of them, HRCo, did not use financial information nor artificial intelligence in their decision-making process so I excluded it from the data of this paper. The case was about restructuring one of their key operations team into several smaller teams. In all the other cases, financial information had roles and the AI discussions were meaningful. ICTCo, however, made their decision so late, that it could not be included in this thesis. The rationale behind the including and excluding decisions are in *Table 7*.

Table 7. *Data rationale*

Company	Included in the data	Rationale
HardwareCo	Yes	Financial information had a key role; AI discussions were meaningful
AnalyticsCo	Yes	Financial information had roles; The company is based on AI; AI discussions were meaningful
ProcessCo	Yes	Financial information was crucial; AI discussions were meaningful
ManufacturingCo	Yes	Financial information had roles; an AI discussion was meaningful
HRCo	No	Neither financial information nor AI was used during the decision-making
ICTCo	No	They made the decision too late for this thesis

This thesis led to a currently unpublished article (Tiitola et al., 2019), in which I am the second author. The article has the same case companies, and therefore some parts, especially citations, case overviews and process descriptions, have significant similarities. Despite the similarities with the paper, this thesis is fully my original work and it provides a more detailed analysis to the research questions as the format does not have any major limitations in word count.

The data set of this thesis consists of four different companies: HardwareCo, AnalyticsCo, ProcessCo and ManufacturingCo. The first two are small companies, third is a big corporation and the last a medium sized company. HardwareCo sells electronic devices with software and their decision case is about production forecasting for 2019. AnalyticsCo offers a data analytics software and the case is about targeting a new customer segment. ProcessCo is in the process industry and they have a productivity investment. ManufacturingCo makes automation systems and their decision is target setting for 2019. A summary of the case companies is in *Table 8*.

Table 8. *Summary of the case companies*

Company	Industry	Revenue (2017)	Case decision
HardwareCo	Software & Hardware	1–10 million EUR	Production forecasting for 2019
AnalyticsCo	Software	0.1–1 million EUR	Targeting new customer segment
ProcessCo	Process	1–100 billion EUR	Productivity investment
ManufacturingCo	Automation	10–100 million EUR	Target setting for 2019

In order to analyze the cases, we conducted eleven semi-structured interviews for different actors. We found key informants within our research group's network. These informants accepted that we could conduct interviews within their organization. We used respondent-driven 'snowball' sampling as we asked the key informants whom we should interview in order to get a comprehensive view of the case. Two researchers interviewed all the informants individually. I was one of the interviewers in all of them; one postdoctoral researcher participated in HardwareCo and ProcessCo cases and a PhD candidate in AnalyticsCo. In ManufacturingCo the postdoctoral researcher participated in the interview with the business controller and the PhD candidate with the business unit manager. Therefore, ManufacturingCo was the only company where the researchers changed between different interviews.

I acknowledge that I based the case rationale more on the structure of the research project than the research questions. Yin (2003, pp. 47) maintains that *'every case should serve a specific purpose within the overall scope of inquiry.'* Thus, the data rationale in *Table 7* is excessively thin. If I would rewrite this thesis, I would make a two-case study of HardwareCo and ManufacturingCo. Those are somewhat similar, as they are about financial forecasting, which would offer an opportunity for *literal replication* (Yin, 2003, pp. 47).

We assumed that every actor had a different perspective to the same event, so we wanted to interview all related persons. The average duration of the interview recordings was 1 hour 39 minutes, but the interviews were naturally few minutes longer as we did not record all the small talks in the beginning and end of the interviews. A summary of the interviews is shown in *Table 9*.

Table 9. *Summary of the interviews*

Company	Title	Language	Interview duration
HardwareCo	Product Development Director	Finnish	1 h 49 min
HardwareCo	Head of Product	English	1 h 54 min
HardwareCo	Procurement Manager	Finnish	1 h 51 min
HardwareCo	Controller	English	2 h 0 min
AnalyticsCo	Co-founder, VP of sales & marketing	Finnish	1 h 39 min
AnalyticsCo	Chair of the Board	Finnish	1 h 8 min
ProcessCo	Investment Controller	Finnish	1 h 50 min
ProcessCo	Asset Development Team Leader	Finnish	1 h 47 min
ProcessCo	Development Manager	Finnish	1 h 16 min
ManufacturingCo	Business Controller	Finnish	2 h 3 min
ManufacturingCo	Business Unit Manager	Finnish	48 min
			Avg. 1 h 39 min

I managed to book interviews with many relevant persons but some of them remained unobtainable. HardwareCo case lacks insights especially from the sales department. A sales director and a salesperson would have brought important information to this analysis. In addition, at least one person from the subcontractor would have benefited the case as well. Despite having only two informants, AnalyticsCo case is not missing any crucial information, in my opinion, since we were able to interview a co-founder and a chair of the board who are part of the top management and the whole company is quite small. ProcessCo, however, misses an informant from the user side of the investment, although it probably does not have a significant impact on the research questions but the overall understanding of the investment process. From the data point of view, ManufacturingCo is the weakest case. Despite the interview with the business controller being one of the best in terms of relevance and context, there is an information gap. The business unit manager was able to give us only the 48-minute interview where we had to rush through some questions, and we used most of the time when the business unit manager explained what kind of target setting system they have in general. Other viewpoints would have been needed for a more comprehensive understanding of the case, but I was not able to get more interviews.

We recorded all the interviews and our contractor transcribed them. We interviewed the product development director and procurement manager of HardwareCo in Finnish and the rest of the informants in English. As you might have noticed, I wrote this thesis in English, which means that I have translated most of the citations from Finnish to English.

I tried my best to remain the original message as unchanged as possible by adding missing words in the brackets and thinking carefully what words should be used. However, especially some jokes were hard to translate, and the quotes may miss some of those. I would like to emphasize the fact that I am not in any way professional translator, but I still believe that the quotes tell the stories of the informants accurately.

We used printed interview guides in all the interviews so that we would not miss anything important. The interviews usually proceeded naturally, and our task was just to steer the conversation, but the interview with the development manager of ProcessCo was more question-answer based. The original interview guide is based on previous projects of the research group, so I have not created it. However, I edited, rearranged and prioritized the questions after few interviews to make it easier to follow. A pragmatic version of the used interview guide is in Appendix A.

3.3 Empirical findings

The fourth chapter of this thesis is devoted to within-case analyses. Eisenhardt (1989) states that there is not a standardized protocol on how to conduct it. She says the within-case analyses usually contain case descriptions. To build on this, I decided to analyze the collected data company by company and to split the firm analyses into three subsections in addition to the overall case descriptions and more detailed decision-making process descriptions. The data analysis ended up being iterative, as the topics and research questions changed during the process. The chapter contains both original, albeit mostly translated, quotes and my explanations. The former represents emic and the latter etic viewpoints. Next, I will explain in more detail how I conducted the data analysis.

First, I went manually through the transcriptions and handpicked quotes that were related to financial information or artificial intelligence. In practice, I started writing the quotes under the three topics listed below in HardwareCo case:

- Financial information driving change
- Financial department as a knowledge integrator
- Artificial intelligence needs.

After I had started to go through AnalyticsCo, I realized that it would be beneficial to edit the second topic since AnatlyticsCo does not have a financial department as it is so small firm and in other cases, the financial department is not addressed as directly as in HardwareCo. Thus, I changed the topic to ‘Financial information as a knowledge integrator’ as it seemed more relevant. Later I realized, as I discussed in section 2.1, that the term ‘financial information’ is not sufficient for studying management accounting in all the cases, as I would not consider e.g. production volume to be 'financial information'. Thus, I changed the term in the first two topics to 'management accounting information'. Another major change was to add 'boundary subjects with AI' as a research question and to add it to the third topic. With some other minor changes, the final topics are:

- MA information initiating decision-making
- MA information influencing decision-making
- Artificial intelligence needs and boundary subjects

If I was not sure if a quote should be picked or not, I always picked it. Some quotes of the first two topics are overlapping, so I decided to place those under the first topic. At this point, I translated the Finnish quotes into English and added some information in the brackets if required for understanding. Here I realized that the subcontractor did not write the transcriptions word by word, so the quotes might not be perfectly accurate when it comes to filler words. When I had gone through all the transcriptions and picked the quotes, I started to write a 'story' around the quotes. I differentiated, as clearly as possible, my own interpretation and the thoughts of the informants. I explained the quotes and created a story with the help of my interpretations and transcriptions. In HardwareCo, I and three other researchers reflected and discussed the findings of each interview in order to create a comprehensive response to the research questions. Among other subjects, one topic was about the differences between financial and (management) accounting information and in which category e.g. production volume falls if any.

I did the data analysis manually, which means that some relevant information from the data is likely missing from this thesis. If I would have the chance to change something from the process, I would use a software such as ATLAS.ti in the data analysis. Coding the transcriptions with as software would have endorsed transparency as I could have made several codes from the same data set. In that way, another researcher could have made his/her own code, which we could have compared with mine. Even without any software or help from other researchers, I could have gone through the transcriptions manually several times and compared the results. Next, I will discuss how I created the synthesis of findings.

3.4 Synthesis of findings

I focus the empirical findings into eight propositions and three hypotheses in the fifth chapter. I divided this synthesis of findings into three subsections, one for each research question. In the first two sections, I use the cross-case analysis technique to illustrate patterns between cases, which increases the probability of novel findings (Eisenhardt 1989). I use special case analysis technique in the last section.

The sections include two types of elements, propositions and hypotheses. I base the eight propositions on the empirical findings chapter. The three working hypotheses are my own guesses on what the explanation for the particular proposition could be. This is in line with Silverman and Marvasti (2008, pp. 509) who define hypotheses as *'testable propositions often based on educated guesses'.* The paper of Bourgeois and Eisenhardt (1988) inspired the structure of the chapter.

Eisenhardt (1989) argues it is important, especially in case studies, to tie the empirical section with the existing literature for better transferability and internal validity. Thus, I made additional literature searches and found some specific studies related to the propositions and hypotheses. I also tried to make sure that the literature review chapter supports the findings. Turning now to the empirical findings chapter, which covers the four decision-making cases of this thesis.

4. EMPIRICAL FINDINGS

4.1 Case HardwareCo

4.1.1 Case overview

The case company, 'HardwareCo' is a Finnish company providing solutions to its customers around the world. The product portfolio consists of physical devices and analytical software, which they sell as a service. There are mainly two different devices, device A, of which manufacturing capacity is limited due to a long lead-time of some of its components, and device B, which can be produced without major capacity limitations. The case is all about making and deciding production forecasts for both devices for 2019. This was the most problematic part of their new and more thorough budgeting process.

Our most important informant, a product development director, selected HardwareCo's production forecast for 2019 for our analysis. A key driver for the selection of the forecasting process was that the procurement manager's and sales department's first forecasts differed dramatically so they made significant changes to the budgeting process. Therefore, it was an important decision for the company since it has a major impact on the balance sheet and the decision-making process was recently renewed. The decision was based on numbers, the outcome was numbers, and the director thought it was an interesting event, which also affected the decision to include it in this thesis.

The planning of this research collaboration started years ago when the director was working in another company. In addition, the head of product had done some educational cooperation with us beforehand. All of these led to this data collection in January 2019. The actors still remembered the forecasting process very well as they conducted the budgeting process in late 2018. Some informants turned out to have interesting backgrounds. For example, the head of product of HardwareCo has a math degree and has a lot of knowledge and experience of AI and machine learning. The story of the controller had some inconsistencies and contradictions with the other informants, so I decided to focus on the other interviewees in the analysis. It was not possible to interview their busy sales director, which limits the data. It is hard for even me as a researcher and interviewer to recognize what part of the budgeting and forecasting was actually decision-making, as the process appeared to be rather chaotic. Nevertheless, budgeting contains many assumptions that are small decisions themselves. At least it is easy to notice, that the case is very complex, which means it provides great data to the research questions.

4.1.2 Overall process

According to the director, the start of the budgeting process was strongly related to the sales department. In a phase, where service delivery budget is calculated, they had to estimate production quantities, because the hardware devices are in the HardwareCo's balance sheet, as they are leased not sold. At this point, the director looked at the amounts and thought they cannot be accurate. In the second budget iteration round, the director decided to calculate a new production forecast based on 2018 sales data and ask the product development manager's own opinion, which was even more radically different from the original estimation. Next, the director, the procurement manager and the product development manager thought about it, and the director asked the financial department if it was beneficial to change it. Their first answer was 'let us go through this budgeting round with the original numbers and you can do your own production forecast'. Then the director made some calculations and told the financial department that the difference between the initial budgeted number and is X million euros (which was a significant amount in the HardwareCo's balance sheet) so the department said that maybe it should be explored more.

> *'-- the difference was [X] million euros in the balance sheet so the people in financial department said that maybe it should be investigated further.' – Product Development Director*

Next, the informants made several iteration rounds to the budget. Later on, the situation was presented to the top management team, which accepted the changes and the budget was then updated. After all, the production forecast for suppliers was different from the budget version, because the procurement manager did not agree with as big changes to the history data. To manage this, all the participants, including sales department, agreed to start following and adjusting both budget and forecast numbers more frequently.

4.1.3 MA information initiating decision-making

As discussed above, the big difference between the original forecast and the calculations based on 2018 sales data initiated the complex decision-making process. Before that, the director started improving the budgeting process because the original numbers did not match the director's and the head of product's gut feelings. The head of product had a feeling that the device B will be selling more than before, and the sales trend supported the idea.

> *'This is how this whole thing started. He/she [the Product Development Director] said "Do you believe in this? Because I need to pay the bill." [laughter] "No." So then we did it.' – Head of Product*

> *'[...] the forecast sits in the sales organization because in theory they are the closest to the customers, they can forecast the fastest and unfortunately the forecast that we received [...] we didn't believe that.' – Head of Product*

According to the director, they were actually forecasting the sales proportion of device A to device B. The revenue goal was widely agreed, but the proportions were not. The sales department had forecasted that the majority of sales would come from device A but the actual proportion had become 50-50 by the end of 2018, which was triggering the start of the new forecasting process.

> *'[It was critical that] the change [in customer demand] was so dramatic [...]. Otherwise we would not have used so much time in this.' – Product Development Director*

The initial forecast for device A, made by the sales department, was rather high. The director said that one of the two people involved in the forecasting had already known that he/she will be leaving the firm and the other one was quite new. Thus, the forecasts were most likely made quickly and/or by guessing without proper assumptions.

> *'But our number and [...] the sales forecast was completely different. And it was interesting because when we went back and challenged sales and say "Hey, what were your assumptions?" they said, "Ah we don't really have assumptions, so we thought this is the best."' – Head of Product*

Part of the reason why the process was changed this time was that there had not been a person with sufficient time to do a well-detailed budget before this new budgeting process. Now the controller could make better assumptions, because there was enough time for communication between the parties.

> *'We have grown so much that this time we had a dedicated budgeting person [the controller] who made it more carefully and had the time to ask questions and make those calculations.' – Product Development Director*

> *'This year we tried to make better forecasts with budgeting.' – Procurement Manager*

The head of product had been participating in both overall and customer specific pricing, which gave some insights about the past and the future of pricing. According to the director, this was essential when the total sales target was converted to the production volumes and further to production costs. The director thinks it was critical for the start of the improvement that the budgeting process was iterative, so the budget was ‘on the table’ many times. The process improvement did not start in the first round, but the importance increased gradually.

> *‘[It was critical that] there were many budgeting rounds […] so the paper came onto my table many times.’– Product Development Director*

Even though MA information appears to be in a key role according to the director, the head of product and the controller, the procurement manager had a different viewpoint. As the agreement with the supplier is based on a specific profit margin, unnecessarily high inventories do not affect the HardwareCo’s finances. Therefore, the procurement manager did not see financial information in an important role.

> *‘We have agreed to a certain profit margin which covers the inventories. […] Therefore, financial information has not been [heavily involved] as our contract do not pressure us into it.’ – Procurement Manager*

After all, I argue that the MA information started the decision-making process together with the iterative budgeting process, although the procurement manager seemed to have a different opinion on it. Next, I further analyze the influence of MA information in the complex decision-making process in HardwareCo.

4.1.4 MA information influencing decision-making

As the management accounting information clearly initiated the decision-making process, it also had its own remarkable impact during the process. In addition to the direct impact, the influence can also be indirect. For example, the following communication and teamwork between the participants, including financial department, is a form of indirect impact of MA information.

All the participants thought open communication was very important. While the controller and the financial department did the budgeting, the product development director argues it was critical that he/she and the head of product were participating in the process. They both brought data and their own point of views on the table.

> *‘[It was critical that] the head of product and I were participating in this process because we both brought data and views [on the table] and we believe in open communication.’ – Product Development Director*

Three out of four informants believe in teamwork, but the head of product slightly disagrees with it. He/she believes that one good and experienced person should make the initial budget and then senior management should give their input based on their experience. The controller is fully behind the idea of teamwork and says that they made the budget as a team. The procurement manager, however, also believes in teamwork but thinks that currently they do not have a common goal, which is a contradiction.

> *'[...] you normally have one guy which is good, has seen a lot, can put something together, and then you have the senior management coming in, because they have a different perspective. They talk to other people. They talk to industry. They have a bit more information that you would have. But and they can challenge and modify assumptions.' – Head of Product*

> *'[...] you have to really combine from different teams' opinion, because we all work together. It's like a team work. We can never just give some decision by ourselves. It's all like a team work.' – Controller*

> *'I think this kind of company is like a [sports] team which shares a common goal. [...] In this case, I have to say that we do not have it and it is a contradiction.' – Procurement Manager*

The previously mentioned iterative budgeting process means that the parties discussed the numbers together many times. From the director's perspective, it was important because they found several miscalculations that improved the overall quality of the budget.

> *'The iteration process led to that we found many miscalculations made by everyone including me which improved the quality of the overall [budget].' – Product Development Director*

The director expected knowledge of the products and offerings from the people in the financial department. These expectations were not fully met as sales of a new product were budgeted to start in January 2019 while the reality is in July 2019 at the earliest. The director thinks the reason was that the new people did not understand enough in order to be able to ask questions about different numbers. The calculations made by the financial department are sometimes too precise for the fact that they are based on gut feelings. The director says it means from the management perspective that they convert conjectures to data. In addition, the procurement manager appears to demand operational knowledge from the financial department as different types of customer orders may look similar from the financial perspective but very different from the manufacturing perspective.

> *'There were many new people involved [...] in financial and sales departments who do not necessarily understand the products and concepts enough. For example, a new [...] product's [...] sales were forecasted to start in January 2019 while*

> *the reality is in July 2019 at the earliest. [...] Maybe they should understand enough in order to be able to ask questions. Here they did not ask.' – Product Development Director*

> *'Sometimes it bothers me that they make really precise calculations in the Finance Department but do not think that it is based on nonsense. So, they convert gut feelings into data.' – Product Development Director*

> *'Renewing orders [which do not require a new physical device] may make the financials look exactly the same but from manufacturing perspective it is totally different.' – Procurement Manager*

The head of product argued that the sales department should not do the production forecasts. Instead, the numbers should be asked from a person who has least incentives in it. According to the head of product's experience, this applies to other industries as well.

> *'[...] sales forecasts by salespeople are the worst forecasts that you can get. And I can tell you because I have been in sales as well, so I have been guilty of the same thing. – Head of Product*

Therefore, it seems that the MA information had a role of knowledge integrator and it was a boundary object, as it got people together to discuss about different forecasting numbers and the assumptions behind them. Budgeting is a key element in the work of management accountants, so the MA information naturally had a big role in it. However, as the outcome was an official and unofficial forecasting numbers, I argue that with better usage of MA information, the outcome could have been just one number if the reasoning had been more solid.

4.1.5 Artificial intelligence needs and boundary subjects

The director would ask AI, what sales leads are saying since it could help forecasting the production faster. He/she would like to know more about the availability of some components, and he/she thinks most the whole budget could be done with the help of AI if it would ask inputs and then iterate it further. The controller would like to have an automated budgeting tool, which would enable him/her to be more professional and efficient at work. He/she argues time could be saved especially from revenue and payroll calculations. The controller says automated budgeting tools are not in use in HardwareCo since they are so expensive. The procurement manager would ask AI how accurate the forecasts have been and whether a big monthly deviation should be ignored or not.

> *'Budgeting could mostly be done with the help of AI. [...] It could ask for certain inputs and then iterate it further.' – Product Development Director*

'[…] the kind of budgeting system we would like to have is make […] all the calculations automatic […] to really save time to be more professional and efficient on the work. I think that's a difference.' – Controller

'So, I would say for that kind of a system it can make like the revenue calculation, and the payroll is more automatic calculated, that can save a lot of time.' – Controller

'[I would ask AI] how accurately sales department have forecasted […] and of course my own accuracy. […] Is a big monthly deviation part of a trend or should it be ignored?' – Procurement Manager

Outside of this forecasting process, the director would like to get more knowledge about the market situation including changes in the competitive environment and behavior of their customers and potential customers in e.g. social media. The director thinks it would be beneficial to know when a potential customer starts a development program so they could offer their services right away. The head of product would like to know what are the most loved and hated features of the products as it would help with prioritization of R&D. Since there are so much engagement data available, the head of product would like to have an algorithm going through all the data and to pinpoint unusual behaviors in order to recognize new customer values.

'I would ask what is the most-loved feature of my product.' – Head of Product

'For example in my job, it would make it so so much easier, because for example the prioritization, of what do we do in R&D would become so much easier, if I know what customers love, not what they use, what they love then I can press the pedal more there. If I know what they hate, I know what I need to go and fix. So, at the moment again all these decisions they are not really based on data […].' – Head of Product

'For me for better decisions, […] I would need exactly this kind of thing, an algorithm to comb through all that engagement data how our customers are using the product and give me these nuggets that hey, you have, 50 users which are using this thing but they are using it 30 times day, at least. This kind of stuff. Because then I can go pick up my phone and call that guy and say "Hey, why are you doing this? Why do you find so interesting that you do this 30 times a day where majority of my user, does it once every second day? What value do you get out of it?"' – Head of Product

The above-mentioned AI needs are presented in *Table 10.* I clarified the needs to be more compact. These needs can be understood also as new boundary objects in their future decision-making processes, if the AI needs are fulfilled.

Table 10. *AI needs/objects in HardwareCo*

Identified AI needs/objects	**Requesting informant(s)**
What our leads are saying?	Product Development Director
Component availability	Product Development Director
Market analysis tool (competitive environment, behavior of existing and potential customers)	Product Development Director
Notification when customer starts a development program	Product Development Director
Automated budgeting tool	Product Development Director, Controller
Forecasting accuracy feedback tool	Procurement Manager
What are the most loved and most hated features of our products?	Head of Product
Unusual use cases of our products	Head of Product

In order to utilize AI in operations, the director says they would need more data from different industries. For analyzing customers, they would need to meet the right company, which does that kind of AI product development. In addition, the value of the data would be needed to demonstrate, for example if it would somehow generate more sales. By contrast, the head of product, who has a math degree, thinks that implementing machine learning is just a matter of resources, as the data for the information he needs is already available. In addition, the head of product argues that a good algorithm plus some behavioral data is critical for service companies. The reason behind this is that it enables better investment decisions.

> *'[For implementing machine learning] we just need resources. That's it. Because data we have available […] so that's not an issue. It's just that, we have couple of data scientists, but again they are busy doing, other stuff.' – Head of Product*

> *'I believe machine learning for decision-making will, especially around this behavioral data for company like ours, because we sell a service, I think this is critical. Because […] when you have a good algorithm, it allows you to take the correct investment decisions saying okay I'm going to, invest a bit more here, invest a bit less here. This is what we are trying to do now. But yeah, we'll get there slowly. It's going to make life so easy.' – Head of Product*

There seems to be several needs for AI and/or machine learning in HardwareCo. All the informants would like to have some sort of intelligent system to help them with their work.

For some knowledge desires, there is already sufficient data available and the implementation is just a matter of resource commitment. As discussed in the methodology section, new expected boundary subjects were not part of the initial research interest. The topic did not emerge in the interviews within HardwareCo. Thus, there is no data on new expected boundary subjects with AI in this case company. Now I will move on to the next case company, AnalyticsCo.

4.2 Case AnalyticsCo

4.2.1 Case overview

The case company, 'AnalyticsCo' is a Finnish company providing data analytics software to its customers mainly in Finland. The product analyses data and supports decision-making by alarming the user when someone needs to do something. One of two of our informants, the vice president of sales and marketing, who is also a co-founder of the company, selected AnalyticsCo’s new sales focus decision for our analysis. The other informant, more recently joined chair of the board, complements the view from the actual decision-making side.

AnalyticsCo has been pivoting its product portfolio for almost 10 years. They ended up serving a niche in the processing industry with their software, which utilizes AI and machine learning. I analyze the decision to target this particular niche in the following sections. The board of directors made the formal decision in December 2018, although it had been informally in action before that. We conducted the interviews in Finnish in February 2019.

4.2.2 Overall process

According to the interviews with the chair and the co-founder, this decision-making process did not have a clear starting point. They used to serve not just different kinds of companies in the processing industry but also in e.g. food industry. The chair states the idea behind it was to gather revenue wherever possible in order to keep the company profitable.

As explained by the co-founder, they used to serve some companies in the processing industry and had thought early on, which other companies are collecting lots of data and realized the opportunities in another segment in the same industry. After that, they developed the software product according to one customer in this field. In addition, the references in the segment helped the sales team to close the deals in the same industry even though they contacted companies in other industries as well. There was some internal debate in AnalyticsCo between the sales and technical teams for three or four years, whether they should serve every manufacturing industry with process data or just this segment. Thus, the offering was unfocused for a long time but naturally became more focused as they closed more deals in the niche. As mentioned earlier, the formal decision was made in December 2019, which could have been earlier in both chair's and co-founder's opinion.

> *'We hesitated internally for a long time whether we have a solution for all the process data [...] or should it be focused to [the niche]. [...] The technical side had a vision that the product would be generalized to everything, but it was felt in the sales team that we do not have the skills to sell for everyone.' – Co-founder, VP of sales & marketing*

Although the process slowly emerged to the specific decision, several critical steps led to it. The chair said that the critical steps were an outsourced market research analysis, obtaining a first good reference from the particular niche, getting angel investments and getting a product development loan. However, the co-founder thinks the critical steps were troubles in sales, realizing that many of the customers were Lean Six Sigma experts from the niche and hiring a new CEO and board members that had expertise in the particular industry.

4.2.3 MA information initiating decision-making

As the co-founder stated, sales had not been at a desired level, which was one of the key drivers for the decision. In practice, co-founder thinks the same phenomenon can be seen also from the number of people in the company, which is about 15 while it should be 300.

> *'[...] our ambition is on a much higher level. We are now about 15 people thus sales have not been good enough. I think we would like to be 300 people, so it is clear.' – Co-founder, VP of sales & marketing*

At some point, from the co-founder's perspective, they noticed that over 60 % of the revenue already comes from the paper industry. As I discussed earlier, the process did not have a clear starting point, which implies that the MA information nor anything else did not have a major role as an initiator, although there were many critical steps that led up to the decision.

4.2.4 MA information influencing decision-making

The chair of the board says that the estimated market size of the particular niche was used during the decision-making process. He/she argues that the focus should be adjusted in a way that would create a market share of at least 15–20 %. This will give the courage to say that the company is a notable player in the market.

> *'The market share should be more than 15 % so it would be good enough. [...] if it is not 15 % or 20 % then the market scope has to be reduced.' – Chair of the Board*

According to the co-founder, the market size is a problem, which has started an ongoing discussion. There are only about 20 factories left in Europe that they have not been able to be in contact in the niche. The co-founder states that if they do not close deals with those at a high success rate, they will have to either broaden the scope or start contacting companies outside of Europe. With this scope, they can keep going for *'at least this year [2019]'.* In contradiction, the chair states that the market size is big which leaves some question marks, whether we were talking about this niche or the industry in general. The first one would implicate that there are some disagreements or misunderstandings in the company.

> *'If you think about the problems, that the decision caused, you could point out that there are not endless amounts of factories in this niche.' – Co-founder, VP of sales & marketing*

> *'The amount of companies that could enter our sales funnel is a joke [in this niche].' – Co-founder, VP of sales & marketing*

> *'And the question was about financial metrics so [...] of course the market size is big [...]. – Chair of the Board*

The analysis of the market size led up to the adoption of a product roadmap thinking, which has been endorsed by the chair. It means that after the market size had been agreed, they estimated how big market share could be acquired, and what product development steps should be taken for that. It is a plan for the next two or three years, which enabled cost estimation calculations. This road map initiated conversations and helped with the targeting decision, since it showed to people that these development tasks have to be prioritized, as not all the customers can be served.

> *'I have been strongly endorsing this product roadmap thinking so we could see two or three years ahead what should be developed and released at certain points and therefore estimate what it will cost.' – Chair of the Board*

> *'As a matter of fact, the conversation went through the product roadmap as it was shown what should be developed for one customer so if we do that how are we going serve another one. Therefore, it was realized that these development tasks have to be prioritized.' – Chair of the Board*

On one hand, the co-founder thinks that there were enough information available and the decision should have been done earlier. The problem was that there were different opinions on how certain the decision should be. This led up to a situation in which there were not enough courage to make the decision.

> *'[...] there has been enough information available... it is more like [...] how much different individuals want to make sure "is it really this, is it really this?"' – Co-founder, VP of sales & marketing*

On the other hand, the co-founder believes that they should have understood earlier to start collecting data on customer needs from meetings with them. Then they could have systematically analyzed the data, so they could have noticed two or three years earlier that virtually all of the customers were Six Sigma people who they should be targeting. In addition, all sorts of internal workshops and strategy discussion would have been easier as they used to be based on just few recent meetings rather than hundreds. The chair reflects that in a public company, they used to have very exact information about the market, but in AnalyticsCo, which is small firm, it was an unknown area at first. Whether there was all the information available or not, the co-founder still thinks that people may believe in what they want regardless of the data.

> *'People create a very biased viewpoint of everything as if we have hundreds of customer meetings, I remember last week very well. If I say we should choose a market segment based on that and another person remembers another event it leads up to a pointless argument.' – Co-founder, VP of sales & marketing*

> *'[When I used to work for a public company] we knew exactly how many factories there were, how much our competitor's and our sales were when we were creating a strategy. For AnalyticsCo it was really weird at first like "Do we need to know these as well?"' – Chair of the Board*

> *'Even if we would have all the information [...] some people may still say, "Well here is the data but I had this meeting last week and the person said this damn thing!"' – Co-founder, VP of sales & marketing*

This section elaborated the role of MA information in the complex targeting decision of AnalyticsCo. Next, I will analyze the case company from AI needs and boundary subject perspective.

4.2.5 Artificial intelligence needs and boundary subjects

Both the co-founder and the chair state they would like to know more about the market with the help of AI. The chair is interested in the market size, its growth rate, competitors and key success factors. However, the co-founder would like to know how many factories are there; how long is the typical buying process; and what the customers want. The co-founder would also like to have a head-to-head competitor product analysis, which could be extended to other industries to show greatest business potentials. These knowledge desires reflect their positions, as the chair is more concerned about general information and the co-founder more sales specific information.

> *'[I would ask AI] what is the market size? – Chair of the Board*
>
> *'[I would ask AI] what is the growth rate of the market? – Chair of the Board*
>
> *'[I would ask AI] who are our competitors? – Chair of the Board*
>
> *'[I would ask AI] what are the key success factors in this industry in order to be successful? – Chair of the Board*
>
> *'[I would ask AI] how many factories are there [in this particular niche].' – Co-founder, VP of sales & marketing*
>
> *'[I would ask AI] how long is a typical software buying process in the paper industry.' – Co-founder, VP of sales & marketing*
>
> *'[I would ask AI] what the customers want.' – Co-founder, VP of sales & marketing*
>
> *'[I would ask AI to produce] a head-to-head comparison with our solution and ten others partly overlapping products so it would show us how our product differentiates. Thus, it could be broadened to other industries as well to show where the biggest business opportunities are.' – Co-founder, VP of sales & marketing*

The above-mentioned AI needs are presented in *Table 11*. I clarified the needs to be more compact. These needs can be understood also as new boundary objects in their future decision-making processes, if the AI needs are fulfilled.

Table 11. *AI needs/objects in AnalyticsCo*

Identified AI needs/objects	Requesting informant
Market analysis tool: market size, growth rate, competitors and key success factors in the industry	Chair of the Board
Market analysis tool: how many factories are there, how long is a typical buying process, what the customers want, head-to-head competitor product analysis	Co-founder, VP of sales & marketing

The co-founder states that it is a contradiction that they do not have lots of data to support their own needs for utilizing AI while their whole business is based on machine learning and data analytics. Especially, the customer needs and desires have not been stored carefully.

> *'The shoemaker's children go barefoot. We do not have a lot of data about these [above mentioned] things.' – Co-founder, VP of sales & marketing*
>
> *'[...] if we skip numbers, all the information like customer needs and desires are poorly documented.' – Co-founder, VP of sales & marketing*

Overall, there seem to be lack of market and competitor knowledge in the company although they had received a market analysis made buy an external company. Thus, they wish that an artificial intelligence could help them in these fields. However, I argue that first they need to work on their data collection procedures so that benefiting from the data would become possible. As in HardwareCo, there is no data on new expected boundary subjects with AI in AnalyticsCo. Next, I will move on to the case of ProcessCo.

4.3 Case ProcessCo

4.3.1 Case overview

The case company,'ProcessCo', is a Finnish firm in the processing industry. This case is about a productivity investment of which pre-study started in the beginning of 2018. After that, it moved on to a feasibility study phase and in February 2019, when we conducted the interviews, the project was in a definition phase. At that point, the execution of the project was planned to start in spring 2019. The investment requires engineering design and new physical components. The main idea of the project is to improve the warehouse capacity.

We were able to interview three different informants individually about the same investment project. These informants are an investment controller, an asset development team leader and a development manager. The investment controller oversees the whole investment project portfolio including maintenance, safety and productivity investments. The asset development team leader's team is responsible for e.g. gathering project ideas and moving them forward in a project funnel. The development manager, however, is part of the asset development team and leads the particular project in ProcessCo.

The investment controller chose this project under our analysis because the project was familiar and the controller had done some work for it unlike many other projects, as the position requires more general portfolio work rather than actually doing e.g. calculations for every project. According to the controller, there are hundreds of projects in the portfolio yearly. The projects and the portfolio is managed through a portfolio management system.

> *'When we started to discuss about this project proposal [...], here [in ProcessCo] these proposals proceed by that they are created in the portfolio management system.' – Investment Controller*

> *'Information, depending on the starting gate, is added there [in the portfolio management system]. The proposals are summed up to a portfolio forecast.' – Investment Controller*

The controller opened the portfolio management system during our interview and showed us quickly how the project had developed with different approvals and documents. Because the process is quite complicated, there were dozens of documents and we did not spend a lot of time on them during the interview, I realized during the data analysis that the detailed chronological story remained somewhat unclear. Hence, there certainly are some minor gaps or mistakes in the described process especially on what documents were created and approvals were done at certain points. Every gate requires multiple approvals from different actors and we were not able to document these, although we saw them quickly on the screen. These limit the data but should not have a major impact on the topics related to the research questions, as the MA information seemed to be widely used in the process. If it was not in a key role, the lack of details might had led to false implications. Next, I will go through the overall process.

4.3.2 Overall process

In ProcessCo, investment projects are divided into several phases, which are called gates. The relevant gates, considering the current phase (G1C) of the case project, are listed below:

- G1A: Pre-study
- G1B: Feasibility study
- G1C: Definition
- G2: Execution

According to the development manager, the discussions of the particular project started in autumn 2017. It was accepted to pre-study in the beginning of 2018. After that, it moved on to the feasibility study and it is currently in the definition stage. The development manager told us they split the project in half, of which the investment controller neither the asset development team leader did not mention to us. At first, the halves were supposed to be in one project together, but some technical problems raised in the other half, which led to the separation decision for scheduling purposes in order to keep the easier half going so they could obtain the first benefits faster.

> *'[The project was split in half] because the profit expectations are so high, and we try to gain benefits earlier.' – Development Manager*

The development manager joined this project at a very early stage, during the last quarter of 2017, as the manager was chosen to be the responsible person for the project from ProcessCo. The person in charge prepares the documents for the decision-making and communicates between ProcessCo and an engineering company, which makes the engineering design. The responsible person also steers the project by making sure it stays on budget and schedule.

The project management software has an internal control system. It does not let projects to continue to the next gate without meeting some requirements and getting approvals. A capex controller ensures a project fits into the budget and then asks a branch manager for an approval.

> *'Our capex controller checks that all the approvals have been made and that the project meets the requirements before it can move on [to the next gate]. The person also makes sure that the project fits the overall expenditure so there is a possibility to question the project if it would significantly exceed [the budget]. After that, the capex controller sends a request of approval to a branch manager. [...] There is internal control in the system so the final approval [from the top management]*

cannot be requested without all the approvals [from lower levels]. – Investment Controller

The project has some characteristics, which makes it unusual for ProcessCo. The team leader states that about 80 % of their investments relates to safety and maintenance of old equipment. The development manager says in many projects they just replace an old device and maybe improve it slightly. In this case, however, they have to create something new that has never been used in ProcessCo and maybe not anywhere else either. Therefore, this investment project is rather rare, and it requires collaboration with unusual parties such as sales, marketing and production planning.

4.3.3 MA information initiating decision-making

The development manager states that the idea for the project came from people who are responsible for buying the raw materials. The investment controller says that there were a shift in the market in autumn 2018. My interpretation is that the market shift was a price change of the raw materials and the company could have exploited it better if the investment had been in place. Thus, it seems that the market shift accelerated the investment process as the preparations had already started almost a year earlier.

'[...] there was a market shift during the end of the last summer [August–October 2018]. We would have liked to sell more but there were some limitations.' – Investment Controller

As the project is a productivity investment, some financial figures such as costs, profit expectations and payback period were calculated at a very early stage during the pre-study. In addition, different technical options have to be studied at this point. Next, a presentation was prepared for a 'panel of judges', and then the plant management team decided to support the investment idea.

'Because this is purely an investment project, some financial key indicators have to be calculated. [...] first, the costs are estimated and therefore profit expectations, which lead up to payback time and so on. Thus, [a presentation] is prepared for a "panel of judges" and then the plant management team decides if this is something that they want to invest in.' – Development Manager

'[...] profitability potential and different solutions to the problem have to be presented [to the "panel of judges"] when the project is about to hit the feasibility study phase'. – Asset development team leader

The project seems to be exceptionally profitable although it is quite small. The development manager also said that besides being profitable the payback period is short. I assume the great profitability made it to stand out from the project pool although there were many other projects waiting for their turn.

> *'In terms of profitability this is a very significant project as the calculated profits are remarkable and the payback period is short. However, as an investment this is not a very noteworthy compared to others. It is a rather small one.' – Development Manager*

Hence, MA information played a key role in the initiation of the project. This is not surprising as it is a productivity investment, which is about improving the finances of ProcessCo. Next, I analyze the role of the MA information in the decision-making process more thoroughly within this particular productivity investment case.

4.3.4 MA information influencing decision-making

As I mentioned earlier, all the information about the project is managed through ProcessCo's portfolio management software. Therefore, the software is inevitably a knowledge integrator and a boundary object as it is the platform for the stage gate model, documents and approvals.

Available resources seem have an effect on the portfolio management level. The investment controller says that if people fear that there are not enough resources for all the intended projects, they put some of them on hold or dismiss them. It was shown to us during the interview that the software has a simple portfolio view on current and planned projects, which seemed to be useful in the overall portfolio management work.

> *'Projects may get on hold if the market situation or other plans change. [...] If the portfolio seems to become too big and people start to fear that, for instance, there are not enough resources available, we start to go through the portfolio. Then some projects may get on hold or dismissed.' – Investment Controller*

For any investment, it is obvious that costs need to be estimated beforehand. According to the team leader, they create the first cost estimation in ProcessCo during the pre-study phase. The development manager brings the numbers together based on past projects and the experience of engineering designers and project managers.

> *'The guess about total costs of a project in the pre-study comes from some of our development managers who has hopefully seen lots of projects [...].' – Asset development team leader*

> *'If there has been similar projects, we can mirror their overall costs. And of course, we utilize the guesses of engineering designers and project managers on the costs when we know what kinds of materials and machines should be bought. Thus, the expected overall costs are created with knowledge and experience. […] then I try to bring the expected overall costs together from different sources […].' – Development Manager*

Profitability is definitely important measurement in the company. All of our three informants mentioned it during the interviews. The development manager says it is calculated at every gate, which implies it is used in the decision-making.

> *'Profitability is assessed at every decision-making process, so all the profitability figures are calculated when hitting the next gate.' – Development Manager*

The investment controller is the owner of the Investment Excel, which is the platform for financial calculations. It ensures that different people make the profitability calculations in the same way, so the projects are somewhat comparable together. An investment period, a write-off period and a tax rate are specified in the Excel calculations, which are in a form of an income statement and a balance sheet. The investment controller is responsible for the detailed instructions on how investments are calculated in ProcessCo. The filled Excel tool is stored in the portfolio management system and therefore comes with the project.

> *'[This investment Excel] works as a template on how financial review is done. Therefore, not everyone does the calculation of profitability differently. […] As an investment controller I have the ownership of the instructions on how the profitability calculations are done.' – Investment Controller*

> *'There is an investment period, a write-off period and a tax rate defined [in the investment calculation tool]. The calculations are done in a form of an income statement and balance sheet.' – Investment Controller*

According to the investment controller, profitability is calculated early on, so the profitability, and therefore the business potential of the investment, can be assessed as early as possible. It is not calculated for safety investments.

> *'[Investment Excel] is made for every [productivity] investment. The first profitability analysis is made during a very early stage so it can be determined whether the project has a business potential or not. […] of course, it is not made for safety investments.' – Investment Controller*

The asset development team leader says that the team prioritizes the projects. If a safety risk is high, the authorities require that it needs to be fixed. The person similarly states that profitability is not important for safety investments. However, the particular productivity investment was thought to be so profitable that it was decided to be endorsed. Therefore, it seems that the asset development team has a lot of power on what cases they are presenting to the panel of judges and what they are not.

> *'It is on our responsibility to prioritize [between productivity and safety investments]. [...] We categorize risks according to which kind of explosion would happen, how many people would die and what is the probability. [...] at a certain risk level, it is required [by authors] that it is fixed during the next possible event. [...] This productivity investment obviously was not prioritized very high in this category, but it was seen so profitable that it was chosen to be implemented as well.' – Asset development team leader*

After all, the team leader argues they have difficulties with the project prioritization. He/she questions if they are able to choose the right projects for implementation from the project candidates. From my point of view, the prioritization problem seems to be complicated as it involves both financial and safety measures.

> *'I think we are now grappling with project prioritization [...]. If there is not enough money and resources for everything, are we able to choose the right ones?' – Asset development team leader*

Both the investment controller and the asset development manager say that the case project has uncertainties because of the market volatility. In practice, it was handled by revising the profitability calculations and discussing the matter. The calculations concerned different market scenarios and costs of capital. The Excel sheet also has a background data set, which contains at least market information. With this information, they have calculated low case, base case and high case scenarios for the investment in terms of US dollars.

> *'[This particular investment] is an extraordinary case since so many revisions [of the profitability calculations] have been done because the subject is so market sensitive. [...] I have here the latest version, which is the fifth revision. Thus, we have calculated different market scenarios with some varying costs of capital.' – Investment Controller*

> *'[...] The background data [...] contains market information etc. [...] which leads up to a base case, low case and high case of the forecasted benefits in terms of US dollars.' – Investment Controller*

> *'There is a lot of more uncertainty on the profitability of the investment in 1-2 years than in half a year. […] We have discussed this a lot where the economics are going and whether this project is profitable or not [after 1-2 years].' – Asset development team leader*

Just as the monetary benefits were thoroughly analyzed in ProcessCo, they have also identified non-monetary benefits. It makes one process much easier, which should have indirect benefits according to the investment controller. However, the calculations include only direct benefits to be on the safe side. They also assessed if the investment would make something harder, but the results were not revealed in the interviews if there was any. Although, there were some safety-related biases against the investment among the end-users, which raised the planning costs and delayed the project.

> *'We have also identified other types of benefits [than monetary]. For example, it makes one process much easier. It could have significant monetary value. In this [calculation], we have taken direct benefits into account of which we can be sure. Then of course, we always have to think about the other side as well. Will it make something harder? […] we discuss that together.' – Investment Controller*

> *'[The safety-related biases against the investment among the end-users] caused delays in the schedule and of course in a way [engineering] design costs increase every time we investigate a [technical] option and something comes up and then we try to find alternatives.' – Development Manager*

Another issue lies with the heavy structure of the investment process. The investment controller states all the projects worth over X euros go through the formal investment process with gates and documents. Three people from an operations management team make sure that these documents are sufficiently made, and they can ask questions about them. This ensures that all the aspects have been taken into account. The investment controller argues this complexity is a good thing since the organization is so big and complicated and there would be issues if information was passed by worth of mouth.

> *'Projects exceeding X euros go through a gate review process. […] in the operations management team there are three people going through required documents. Responsible persons [e.g. development managers] create the documents and they are used for justifying the project and making sure that certain aspects have been taken into account. The team can then ask questions.' – Investment Controller*

> *'Maybe it is required to have a heavy structure [behind this investment process] because the size and complexity of this organization. It could fall into a pitfall if information was passed by word of mouth.' – Investment Controller*

Nevertheless, the development manager states the heavy investment process leads up to higher costs and especially in small projects, the engineering costs may be remarkably higher than the cost of equipment and labor. This is not usually visible for the decision-makers i.e. panel of judges. Yet they have discussed the matter together how they could be more efficient.

> *'It is not necessarily visible for the decision-makers that all the projects follow the same [heavy] investment process but it is more visible to the engineering supplier. Moreover, it increases the project costs, which is thus visible to the decision-makers [...] the share of the machines and labor of the total cost is not necessarily high as the costs accumulate from other sources. In a small project design and other costs stand out. [...] We have discussed together how we could be more efficient.' – Development Manager*

At the same time, the team leader says the company struggles with lack of engineering workforce such as automation engineers, project managers and contractors. My interpretation is that the unnecessarily complex investment process plays its part in the resource shortage.

> *'There are not automation designers available. Whatever you pay there just are not. [...] The order books are full for many [years]. Designing resources, project managers [...] and presumably contractors.' – Asset development team leader*

My construction is that the team leader's and the development manager's risk-taking capacities is somewhat higher than the investment controller's is. The team leader says their investment model does not allow taking risks by planning in a leaner way, which could bring the profits faster. Hence, the problem could be solved by rethinking the above-mentioned project value X, which defines whether the project goes through this investment process or not. In addition, creating a parallel investment process especially for investments that do not possess big safety risks, may solve the problem. This new process could be leaner, save engineering hours, and therefore help with the lack of resources.

> *'Mainly it is better to be sure [that the plans are well made] but if we wanted to get profits faster maybe we should be ready to take risks. Our investment model does not allow taking risks on making a less thorough planning phase.' – Asset development team leader*

Despite lots of communication already happening between different parties, it could be improved further. The team leader states that the team should have conversations with the marketing department more often. Sometimes they ask for something to be in action in a month, and the investment process cannot even create a decision during the proposed period, not to mention the implementation. My previously recommended new process idea could also help with this problem.

> *'We should discuss more regularly [about these productivity investments] with the marketing department. [...] They are like "we have this fair next month and we need this and that". We cannot even make the decision in one month.' – Asset development team leader*

The development manager would like to further promote the understanding that the particular productivity investment do not necessarily bring any benefits to a single production are or a person but improves the company's overall performance. My interpretation is that this productivity investment is not seen as important as e.g. safety investments are and thus some parties think it a reason for not carrying it out at all.

> *'[The most important thing that all the stakeholders should understand] is that this is purely a productivity investment so it does not necessarily bring any benefits to a single production area or a person [...] but it is all about "common good" which improves the bottom line of the company.' – Development Manager*

Hence, it seems the MA information created many discussions and therefore had an important role in the decision-making process. Profitability calculations seems to be especially important in ProcessCo's decision-making culture. Next, I will analyze the case company from the perspective of AI needs and boundary subjects.

4.3.5 Artificial intelligence needs and boundary subjects

The current situation in ProcessCo is that they have not utilized AI in their investment process. However, the investment controller, who studied mathematics as a minor subject at a university, says they have AI projects on customer behavior and technical operations. The investment controller states it would be interesting to have a neural networks model to improve their overall portfolio profitability. My interpretation is that the investment controller is willing to start a project on building a neural networks model on the overall profitability. Other AI solutions could be about inventory turnover, sales and markets. The other three needs were not further determined as we did not ask him/her to do so.

> *'We have not built models [neural networks] on our overall profitability yet [...]. Of course, it would be interesting to see how it would solve the problematic nature of it.' – Investment Controller*

> *'I would be interested in [AI solutions about] inventory turnover, sales and markets [...].' – Investment Controller*

> *'We have ongoing AI projects about customer behavior and [on a technical operations level.]' – Investment Controller*

The asset development team leader would like to get more information from AI about their resource availability and project prioritization. Other needs are a visual tool for showing the statuses and schedules of different investments in different plant areas. The team leader also desires information on resource utilization of subcontractors and resource shortages on projects with red highlights on issues that should be addressed. In contradiction to the previously mentioned problems with project prioritization, the team leader argues that 'There would be seldom a need to ask whether to implement a certain project or not.' I think the person meant with the quote that a 'go' or 'no go' answer for a project is not needed on an operational level because the comment would be completely opposite than the other statements if it was meant to be on the project prioritization level. It is also very interesting that the asset development manager, who does not have a mathematics or other AI related background, thinks that AI may not be the right tool for the needs described above.

> *'[I would ask AI] do we have enough resources [for a project]? And about the prioritization [of projects].' – Asset development team leader*

> *'It is not necessarily an AI problem, but it would be wonderful to have a report on which investments we have on a certain plant area, what are their schedules and statuses. A visual presentation that could be easily edited. [...] There would be seldom a need to ask whether to implement a certain project or not. The answer should be like what projects do we have here, what is coming, what subcontractors are planned to be used, what projects lack engineering designers and what is our resource status, how many projects a designer has and red highlights on bottle necks.' – Asset development team leader*

When we asked the development manager, what the person would ask from AI, the answers were more general business needs than actual AI problems. The problems relate to their project management model, which seems to be too complicated for some projects, which plays its part in the lack of resources. One ambition was on how to manage projects more straightforward and efficiently.

> *'[I would ask AI] how to manage projects more straightforwardly and efficiently. In terms of scheduling, resourcing and costs. In addition, in this kind of plant.' – Development Manager*

> *'I would reconsider our investment model more thoroughly by thinking what should be done in different phases of different projects. Is it wise to have all of them to go through the same model or should they be categorized maybe in terms of monetary value or complexity etc.? […] personally, I think some phases or documents could be excluded in certain projects. It could also help with the [lack of] resources' – Development Manager*

Further questions revealed that especially relatively low-cost maintenance investments, where parts are more or less just replaced, could be simplified by reducing the amounts of phases and documents. The development manager states that they could 'survive with fewer decisions' which is rather ironic way of saying that the current situation is not good.

> *'Maybe these maintenance projects, which are more or less one-to-one renewals [could be more straightforward]. We are talking about [inexpensive] projects […] so there is definitely room for rationalizing. […] the decision-making process do not need to be so complicated because we could survive with fewer decisions.' – Development Manager*

I gathered the AI needs to *Table 12* and clarified them to be more compact. These needs can be understood also as new possible boundary objects in their future decision-making processes.

Table 12. *AI needs/objects in ProcessCo*

Identified AI needs/objects	Requesting informant(s)
Neural network to improve profitability of the project portfolio	Investment Controller
Inventory turnover improvement	Investment Controller
Market knowledge	Investment Controller
Sales tool	Investment Controller
Resource availability (both internal and subcontractors')	Asset development team leader
Project prioritization	Asset development team leader
Visualization tool for project statuses and schedules	Asset development team leader
Resource shortages in projects	Asset development team leader
How to manage projects more straightforwardly and efficiently	Development Manager

Despite majority of the ideas not being necessarily AI related in practice, the development manager says the nature of some software tasks are simple and repeating. These could be reduced by robotic process automation (RPA). This is not either a clear AI problem but at least little more towards it. However, RPA could bring direct benefits with increased capacity but also indirect benefits such as improved employee satisfaction.

> *'Yes there are, I suppose, [some routine tasks that could be automated]. Using some of those [software] systems feels like […] very simple and repeating […] like reading rows or adding there some information.' – Development Manager*

Therefore, many of these so-called AI problems seem to be anything but actual AI problems. I think solving the needs such as the visualized status of project resources or the new project management model does not require artificial intelligence. The resources could be better managed with e.g. a simple Gantt chart software, which is far away from a meaningful AI solution. However, improving the overall profitability of the project portfolio could be possible with AI, but rethinking the investment process might be here the low-hanging fruit. As in HardwareCo and AnalyticsCo, there is no data on new expected boundary subjects with AI in ProcessCo. Next, I will move on to ManufacturingCo, which is the last case in this thesis.

4.4 Case ManufacturingCo

4.4.1 Case overview

The case company, 'ManufacturingCo', is a Finnish firm in project business. Its revenue is 10–100 million EUR and its offering consists of equipment and services. The organization (further sometimes called 'group') has four business units. The decision-making case is about target setting for 2019 with emphasis on one business unit. The budgeting and target setting processes are rolling so they are updated monthly. Managers update forecasts quarterly.

> *'As the closing is done here monthly, we update our targets [at the same time]. For example, new orders increase the order backlog forecast for the rest of the year. […] we have a rolling forecast, so everything is updated by accountable managers of cost centers four times a year […].' – Business Controller*

We were able to interview a business controller, who was responsible for gathering all the information to a profit and loss statement (further called 'P&L'), and a business unit manager (BU manager), who was closely participating in the process. They form the management team of the business unit with heads of departments. The data is very limited as we were not able to interview the heads of departments, of which quantity remains unknown.

'I am always really strongly involved in the forecasting […] and at the end of the day I am responsible for it. When a manager gives a forecast, I have to inspect it and then accept it like it is OK. In addition, very often it is like I go through them and ask if the person has noticed that someone has to be hired or something like that. Therefore, I get somewhat information during the forecasting process, so I somewhat know what is happening in different departments. – Business Controller

The interview with the business unit manager was very short with the length of 48 minutes. This implies that the data tells the story mostly from the controller's perspective. We could not reveal any significant disagreements between the two informants, so one could ask if the process actually was that smooth or if the data just is incomplete. However, my intuitive reaction is that the business controller was not hiding anything, but the analysis would have benefitted greatly from at least one interview with some of the heads of departments.

4.4.2 Overall process

According to the business controller, the process started with a workshop with the management team of the business unit where they looked at their order backlog for 2019. After that, the controller made the first revenue estimation. In practice, the person checked the anticipated backlog at the end of 2018 by product categories and modelled the revenue in Excel. X percent was added onto 2018 sales which resulted in salesforecast of 2019. ManufacturingCo uses percentage of completion revenue recognition model in some of its projects and these revenues are modelled at this point. The process required lots of iterations and discussions between the business controller, managers and head of departments. The business controller states the business unit business unit manager is an important information source as he/she makes also good guesses.

'There were discussions [between me and] the managers, heads of departments, iterating, in practice changing ideas or me having a question and then I go discussing it with a manager. Then we discuss it and the understanding of the topic is improved for both. Moreover, our business unit manager has a very good view widely [over the organization] so often at the end of the day we are discussing with [him/her]. [He/she] gives information or makes guesses, very good guesses. But you have to navigate a lot in the organization […] and maybe know the people who know about these topics.' – Business Controller

The firm had already sold almost all the capacity of 2019, so the challenge is to deliver them. Hence, they started to go through different product categories by finding out how much engineering design hours are required and how many new employees they have to recruit, which led up to some investments and increased fixed costs. When they had calculated the projected revenue, the controller looked at their sales margins in different types of projects and fixed costs of 2018. Next, he/she estimated how the costs are likely to change in 2019 because of investments and recruitments. This led to the first version of P&L.

Next, the business controller and the BU manager started to iterate it further as e.g. R&D were not fully addressed. The BU manager used intuition as the revenue goal seemed to be too high compared to history. In practice, they made some delays to the percentage of completion models. At least one head of department told them that the revenue would not be as high as it was modelled. After these modifications, they were satisfied with the P&L and it looked achievable. This was a probable case and then they created a best-case scenario and a worst-case scenario.

> *'[...] when we had created the first version, we created two other scenarios where we first verbally described, "Okay this scenario means that a hard brexit happens, sales decrease, and blah blah blah."'– Business Controller*

At this point, the targets of the four business units were sent to a group controller who thought about the targets of the whole group. According to the business controller, they made some changes to spread the risks, as not all the units are likely to meet their initial targets as planned. The group controller made then a proposal for a managing director who made the final decision for the targets. Now I will analyze MA information in an initiator role in this target setting process.

4.4.3 MA information initiating decision-making

As stated by the business controller, this kind of target setting process was new to ManufacturingCo. Earlier it had been done in a more top-down and intuitive way rather than this bottom-up based on numbers and modelling. The new process emerged when the business unit manager asked the controller to create the initial numbers of the P&L by intuitively modifying the last year's numbers as it was done before. However, the business controller was not able to do that, as it was the person's first time and the experience in the company was limited. Therefore, the only possible way was to calculate everything. At this point, the following process was unclear because the process was completely new.

> *'Earlier [this target setting] has not been done as number-oriented as now. Before the strategy was going only qualitative, like "yes we can make 110 million [in revenue]". – Business Controller*

'We were having this workshop when [the unit manager] asked me to create the initial numbers, the initial P&L, and earlier the P&L has been created by […] thinking "this will increase, and this will decrease a little". Thus, a deeper understanding behind the numbers has not been sought so they have been created by guessing. […] that was out of my line as I do not have enough understanding for making those guesses and I do not believe that many others have either.' – Business Controller

'I was asked to make the initial P&L […] I did not see any sense in that I would have just guessed the number as I am quite unconfident in principle if I do not have good reasons. If it [the P&L] should steer the operations of the whole business unit, I think it cannot be based on guesses of a recently graduated business controller. – Business Controller

The strategy process should steer the daily operations so it is not just that the management team goes to a summer house for a week to drink and then say [what should be done]. I think it should have a real value for the business and it will not be good if it is done half-baked […]. – Business Controller

The business controller points out that the calculations started from the bottom, and in practice from revenue. They had been measuring profitability on the business unit level earlier but now the business controller calculated profitability for all the project types. Another driver for the change was an increased amount of business controllers in ManufacturingCo. The group controller used to be the controller for all four units but now the business controller is in charge for the controller function in the particular unit. This means there is much more controller resources available for the unit, which made it possible to create the P&L more carefully than before.

'The amount of business controllers has increased. Before [the group controller] has been the controller for everyone in this group so the time allocated for creating numbers for a single business unit maybe was not as long as it is now.' – Business Controller

The BU manager says ROI calculations are made to every project they have, so MA information seems to have a big role in the initiation decisions of projects in ManufacturingCo. However, the comment does not directly address the target setting case, but more broadly to the management culture of the company.

It depends on the project but yes, there have to be ROI calculations in the background, so we start from what kind of profitability potential there is and how much should be invested. In addition, we have product development projects, in which *we always make business case analyses and estimate what kind of ROI could be achieved and what is the risk distribution. So yes, financial information has a big role in the initiation decisions. – Business Unit Manager*

Thus, MA information somewhat initiated the new target setting process. The process emerged as the business controller was not able to set the targets with the previous intuition method. In addition, the increased amount of available controller resource had its impact. Next, I will move on to the next topic covering how MA information affected the decision-making in this case.

4.4.4 MA information influencing decision-making

The business controller states there used to be problems with the previous targets. People were not committed to the targets, as they were guesses. It was hard to hold managers accountable for them, because one could always argue it is just a guess. In addition, the business controller argues that if probabilities from statistics are not considered during forecasting, your mood of the day may affect the targets. My interpretation is that he/she means that they are converting gut feelings into data to some extent, as someone has to come up with the probabilities.

'If you think about the impacts [...] we gave a solid base for the top-level numbers on how we set the targets, so it is much easier to communicate downwards and to hold people accountable for meeting these targets.' – Business Controller

'Previously the management team was not committed to the numbers, as they knew they were guesses [...]. If it looks like a target will not be met, it is much easier to disengage from it by saying "someone made a guess, so I am not really committed to it."' – Business Controller

'I think the guesses are based on feelings like 'our sales are really high' or 'we have a really good project going' [...] When probabilities from statistics are not thought it may have an effect how good day you have had if you [decide to] increase the forecast.' – Business Controller

After creating the bottom-up targets, the business controller says the level of commitment has raised. Nowadays it is easier to hold people accountable even at lower levels. He/she argues that the accuracy and rationality of the numbers made it possible. The business controller states it is important to break the financial targets down to the operational level so employees can understand them and thus meet the targets.

'Now that we have thought about these targets together and spent a lot of time on it at a management team level [...] everyone is probably more committed to them.

> *Therefore, people at lower and lower level is much easier to make accountable for them as the numbers are accurate also at the top level or they have been created rationally.' – Business Controller*

> *'I agree with it [that financial forecast is a tool for operations management] and that is how it should be. Like thinking what we would like to be during this strategy period and then break it down what does it actually mean. The targets cannot be met […] if the understanding is not developed; if we do not really understand how they can be met, they cannot be met.' – Business Controller*

The new targets had a remarkable impact on HR. One of the key outcomes was that the actors thoroughly discussed and understood the recruitment needs during the process. They identified a contradiction between the recruitment plan and the projected needs and they managed to solve the problem. However, the business controller had to re-member HR many times, and MA information certainly had an important role in it. The sales had increased 80 % in two years, so the pressure on HR was substantial.

> *'[…] our sales have increased about 80 % in two years and it will show in our revenue next year. In practice, our organization have to grow a lot. So, I think the understanding that something needs to be done [in HR] in order to be able to de-liver [the sold projects] was not formed until we created the numbers from the bottom and discussed them with the management team.' – Business Controller*

> *'I remember many discussions with […] management team members when I looked at their HR forecast and then told them to "remember that we calculated how many employees we need next year so that we are able to deliver and there is only this much employees in the plan which goes to the HR department." Then I asked, 'why there is this gap between the plan and the needs?' […] it will definitely improve the readiness from the HR or resource perspective.'– Business Controller*

Sales margins are important metrics in ManufacturingCo. The business controller argues it is a big difference in operations whether the targeted sales margin is set to [Y] or [Y+1] percent. My interpretation is that there have been internal debates on how to set these targets. The business controller also states there are problems with calculating the sales margins for product categories. The business units and areas may conduct some work of each other and the projects may be sold internally. Thus, it is a complicated task. In addition, the business controller has to gather data from emails and the whole process requires lots of manual work. He/she states their data management is not in a good shape. In line with my previous interpretation on converting gut feelings to data, the business controller says people are good at guessing and a guess at a low level becomes good at high level.

> *'For example, sales margins are so important for the profitability of the year. Determining them to [X] or [X–2] or [X–1] percentage may appear really insignificant, but it is hell of a difference for our operations whether we get [Y] or [Y+1] percent. If our sales margin is [Z] percentage and someone argues that we should have [Z+3] percentage, […] what should we do if we have done everything to get that [Z]? So how on Earth could we get [Z+3] percentage?' – Business Controller*

> *'[Calculating] our sales margin for product categories [is a bottleneck]. It is really hard […] For example, the outcome of this [area] business unit is not the profit of this area as we may make here some work of other business units. We may enter a project in [another country] as we have internally sold it there and [a branch of the another country] sells it to the customer and the outcome belongs to this unit here. […] We would like to know all the time what the outcome of the product category in this month is. This is surprisingly hard […] I have done some Excel tools, which I have used for calculating them, but it is a really big task. [I have to] consolidate data from emails what outcome has counted where. And it is also exposed for miscalculations.' – Business Controller*

> *'Data collection was difficult to some extent because […] let us say the quality of the data or we do not have that kind of data available, so our data strategy is not in order. For example, it is really hard to get the basic profitability data from different product categories. […] However, we were able to get access to those [required information] when the information is concrete enough, as good guesses emerge because people roughly know what they are, although it does not say it anywhere. […] A guess at the low-level becomes pretty good at the top-level.' – Business Controller*

ManufacturingCo pays incentive bonuses to its employees. The bonuses are paid based on EBITDA. Thus, the target setting is somewhat important to everyone. My construction is that it might have an effect on the targets, as a lower EBITDA target leads up to bigger bonuses, if the operations stay the same in both cases. They update the incentive target yearly.

> *'[…] we have the target where we promise to the board in the beginning of the year what we want to do and in practice the incentive bonuses are based on*

EBITDA so when EBITDA exceeds a certain level, [X] percent is paid for the employees.' – Business Controller

According to the business controller, the targets are transparent. However, the target setting process is not transparent as he/she thinks it is complicated and thus hard to communicate and understand. For communicating the targets, they just had a workshop for about 50 employees, mainly managers, where they discussed the targets and how to achieve them. For others, they have monthly infos, in which they go through profits of the month and the impacts on the targets.

'The targets are transparent, yes. […] In practice, we had a workshop in [this] business unit with about 50 people last week or the week before where we communicated the goals and thought how to achieve them. In practice, there were some kinds of managers and eminent or important persons from this business unit.' – Business Controller

'About the [target setting] process, I am not saying it is very transparent to the organization so it can be hard to understand as the target setting is not a little process so it can be hard for the organization to understand it as a whole or hard to communicate.' – Business Controller

'[…] we have monthly infos at the group level and also in business units or at least in [this] unit. Usually we go through the profits of the month […] and at the same time how does it affect the target and what is the forecast, like are we exceed or below the target in the forecast.' – Business Controller

The business controller would develop the target setting process by tightening the connection between strategy and operational planning. It means that if one sets a target, an operational plan should be created instantly in order to achieve the goal. He/she gave an example that a target may require more work hours, which means that two more employees have to be recruited and that the recruitment process should start next month. This example seems to continue the above-mentioned HR problem discussion.

'[I would develop the target setting process by having] better synchronization so that strategy would become operational planning […] as they should go hand in hand so what we plan in strategy should have a big effect on operational planning. […] the mentality is often like making the strategy and being excited […] and as soon as the operative hat is put on and daily tasks are being performed, […] not everything but a big part of [the strategy] is forgotten.' – Business Controller

'In practice, I think [the development happens] when the understanding [of the target setting process] improves […]. "These targets that you are setting have an

> *effect as in order to meet them in means that your department has to provide this many hours [...] and it means you need two persons more next year and in order to get two person more next year you have to start recruitments next month [...]." It is like when you start to see the connections, I think it is about going through [the target setting] process and talking with people.' – Business Controller*

As the business controller states in the quote above, the development should start from better explanation the target setting process. Another area for development is better understanding of the profit and loss statement (P&L), what kinds of effects operational decisions have on it. In addition, the business controller argues that the heads of departments cost awareness is not at a sufficient level.

> *'[People should understand] the overall view [...] of the P&L [...] like "if more people is hired to my department, which row [of the P&L] does it affect?" If I am a person from finance and I hire more people here, it goes to the admin row. [...] After that, it is [important] to know well your own department and how does it affect the overall view. In practice they [department managers] know their departments very well so it is about understanding the connections [...]' – Business Controller*

> *'People [head of departments] do not fully understand what kind of cost structure they have.' – Business Controller*

The business controller says they have been able to get along with ad hoc analysis as their financial team is small and everyone knows each other. The work is sometimes based on knowledge on what kind of information is in another person's Excel file. He/she also acknowledges it may not work in a bigger organization.

> *'We have still been gotten along with ad hoc analysis, so the information has been somewhat easily available. Our finance team is quite small, so we somewhat know the business environment. Therefore, I know where to get the data and even if it is in a [group controller's] Excel. I know it is there and I can get it. I can check from the person if the data is valid. It might not work in a bigger organization [...]. So if we would get two or three more business controllers, it would not work anymore because [people] would not know anymore.' – Business Controller*

MA information had a significant influencing role in this target setting process, at least from the business controller's perspective. As I mentioned earlier, I was not able the interview e.g. head of departments as their views may have different tones. The interplay between the targets and operations seems to be important for the business controller.

Next, I will move on to the last section, in which I analyze the case from AI needs and boundary subject perspective.

4.4.5 Artificial intelligence needs and boundary subjects

Unexpectedly, the business controller told us he/she is currently studying machine learning while working. He/she would like to learn the core programming and mathematics skills. Combined with his/her financial skills, the interview got even more informative than it had been before this section.

> *'I think this [machine learning] is a really interesting area and I believe there are lots of opportunities. I am studying machine learning as much as I can while working. I am interested in learning the core knowledge on programming and mathematics.' – Business Controller*

The business controller has thought how they could utilize AI in practice. He/she would like to identify what parameters affect their sales margins. However, he/she argues their master data has serious issues. This means it is not possible to get the answer, although it is technically possible.

> *'I have thought [...] how we could utilize artificial intelligence in practice. [...] We could identify [...] what parameters affect our sales margin. If the quality of the master data was good, we could import it to a software and analyze the correlations. But as our master data is not in order it is hard to see the situations where machine learning or artificial intelligence [could be used] because it is so far away from being concrete [...].' – Business Controller*

As ManufacturingCo sells complicated projects, the business controller would like to know what kinds of combinations of their offering are fatal for their supply chain. He/she continues that also knowing how they could be improved and why they are problematic would be helpful. The business unit (BU) manager has a similar wish, as he/she would like to have reports on abnormalities e.g. which project will fail next so it would be useful to have those signals earlier with the help of AI.

> *'First, [I would ask AI] to give some parameters for sales [...]. If we [would] know something at the point of sale, which we cannot yet recognize, like "this combination is really fatal for our supply chain." Finding those. Then, by utilizing the same data, what the combinations are, how can we improve them in the supply chain, why these are hard for us when we lose money.' – Business Controller*

> *'I would like to get alerts on abnormalities or some reports on things we humans notice too late but neural network would spot much earlier. So "tell me which*

project will fail next" would be really useful information if we would get signals of it earlier.' – Business Unit Manager

In addition, the BU manager would like to know answers to sales-related questions like which customers should they contact or focus now. He/she would like to have also some financial answers e.g. how much their prices and procurement costs increased. After that, he/she argues they would replace controllers with AI if they had that. My interpretation is that it was more or less a joke. However, I think they could obtain the financial numbers without AI, but it would require better master data management.

'In sales I would be interested in questions like "Which customers should be contacted now" or "On which customers should we focus more now?"' – Business Unit Manager

'And of course, financial indicators like 'how much our costs increased last year?", "how much the procurement costs increased?" or "how much our prices increased?" which would replace a controller with AI if we had that.' – Business Unit Manager

I gathered the AI needs in ManufacturingCo to *Table 13* and clarified the them to be more compact. These needs can be understood also as new possible boundary objects in their future decision-making processes.

Table 13. *AI needs/objects in ManufacturingCo*

Identified AI needs/objects	Requesting informant(s)
What parameters affect sales margins	Business Controller
Profitability forecasts	Business Controller
What combinations of the offering are fatal to the supply chain?	Business Controller
Which project will fail next?	Business Unit Manager
How much our costs increased last year?	Business Unit Manager
How much our procurement costs increased last year?	Business Unit Manager
How much our prices increased last year?	Business Unit Manager

Just like the business controller, the BU manager is also worried about their data management. He/she is aware of the classical 'garbage in, garbage out' process. His/her solution would be to fix the data management and warehousing first before investing in analytics tools. The BU manager states these will definitely on their X-matrix along with BI-tool development. The X-matrix is a Lean methodology tool, which they use for visualizing key strategic initiatives. Thus, the topic seems to be gaining some momentum in ManufacturingCo.

> *'Starting at the base data, the output of it [AI] will not make sense if the base data is not good. So master data management, cleaning the data, warehousing the data in some modern way, and bringing some analytics tools, which are developing rapidly, on top of it. There are still many steps to take [before I can use AI in my work].' – Business Unit Manager*

> *'I am sure that data governance and developing BI-tools further is something that will be in our X-matrix this year. We will invest more in those. – Business Unit Manager*

The BU manager says they have problems with their portfolio management. The milestones are not checked actively, which distorts the lead-times. He/she acknowledges that they should continuously update a project management system so they could have real-time information on project statuses. Another data-related problem lies with the delivered projects of which documentation is not updated. The BU manager argues they are losing business opportunities of their life-cycle services, as the data would be important for sales and marketing automation.

> *'One big goal for our control mechanisms is to improve the project portfolio management so that we would continuously have real-time information on the overall status of the portfolio. This requires that the project management system is continuously updated so we would have reports based on this data which would give us a view on what kinds of corrective actions should be done. […] e.g. milestones are not checked actively and timely enough which distorts the lead-times.' – Business Unit Manager*

> *'Another example, […] the information sheets of delivered systems are very important for sales and marketing automation in our life-cycle services and if it is not well updated, we lose business opportunities. And I have a lot of other examples as well.' – Business Unit Manager*

According to the business controller, the most important thing in target setting is the understanding of how to meet the targets and to think about it. He/she argues that there is a risk of black box if they neural network would provide the targets. The current manual way ensures that they are analyzing the causes in addition to the numbers. In addition, it helps with information flow inside the company e.g. knowing what others are doing. Thus, the business controller does not like the 'monkey work' but acknowledges the need for its benefits.

> *'It is a probably the biggest thing in the target setting that we understand how to meet the targets and that we think about it. It would be great if someone [neural*

network] just gives them to you but [in this manual way] you can analyze the causes, so it is not just a black box telling, "here are your numbers".' – Business Controller

'I do not enjoy making these analyses as it is sometimes monkey work. […] the [target setting] process would be good to go through in order to synchronize the organization […] and enable information flow, which is really important, to understand what others are doing, working towards a common goal and being on the same page about those things.' – Business Controller

At this point, our interview with the business controller naturally emerged towards boundary subjects with AI. He/she would be 'completely satisfied' if AI could do e.g. monthly closing for him/her. However, he/she raises the question who would interpret and understand the AI analyses if they would have them available.

'But who would interpret and understand the [AI] analyses? I would be completely satisfied if there was AI that could do e.g. the monthly closing so that I would not have to. I could just take the ready-made data or figures like "it looks like this" and then analyze it further. So, I do not have anything against that AI would come and automate many tasks like those. But there has to be someone who understands what it produces.' – Business Controller

The business controller states it would be good if AI would give straight answers. My interpretation is that he/she thinks AI should have an answer machine role (cf. Burchell et al., 1980). Currently, he/she is manually making analyses and the interpreting them to people. If everyone could use and understand AI analyses, he/she would have other work to do and his/her position could change towards teaching others to use AI.

'I think it would be really good if it [AI] would give straight answers. Now […] people ask me and then I make analyses and then interpret and go through them with people. However, let us say if we had this utopia where everyone could use and understand cluster analyses or other things that AI can provide; I think I would have other things to do. I do not feel it gives any more value that I do manual tasks that a machine could do. It could be like that I would teach people to use AI or something like that.' – Business Controller

I identified some benefits of the current manual target setting process above. The business controller states that there are some other problems in the transition to working with AI. First, their operations have been based heavily on feeling as people have learnt their job by doing. There have not been analytics tools available. Second, one should be able to understand if AI could help with the problem and one should be able to ask the question.

> *People have learnt by doing and there has not been that kind of analytics tool in it. In my opinion, doing things have been based heavily on feelings.' – Business Controller*

> *'It is quite a big change […] like when you have a problem you […] should be able to understand that AI could somehow help you and you can ask it.' – Business Controller*

The business controller argues that the AI technology should advance a lot before you could ask questions that you cannot describe well. Moreover, when you have the answers, you should understand what it means and how it emerged. This should be solved before AI can be used in management. He/she would deal with the contradiction by being an intermediate between AI and managers. Thus, people would ask him/her the questions and he/she would describe the problem to AI. Then the business controller would explain the answer to the person.

> *'[The AI technology] must advance a lot before you can ask for a solution to problem which you cannot describe very well […]. Moreover, when you have the solutions, you have to understand what it offers and why. Solving this is something […] what should be done before it could be a management tool. At the moment I think I could be the one that people would ask me […]and then I could be a filter that describes the problem to AI which gives the answer […] and then I could explain it and answer the question […].' – Business Controller*

The BU manager, however, represents those who would be asking the questions from the business controller. The BU manager states he/she would have doubts towards AI at first, if it were in use. Experience on the benefits and the reliability of the new information would be required before its weight in decision-making could be increased. He/she would try to verify the information in another way and if the AI would be powerful enough, he/she would ask it why and how it provided the information. My interpretation is that his/her knowledge on the AI capabilities is limited, as he/she seems to have a desire for superintelligence.

> *'At first, I would have doubts but if there was experience that the information brings benefits and it is reliable, I think the weight of it in the decision-making could be increased. […] I would try to verify the information another way first and if the AI would be powerful, I would ask it to prove why the information is like it is and what kind of logic there is behind.' – Business Unit Manager*

However, the BU manager recognizes that RPA could be a low hanging fruit for them as AI creating new information is relatively far away because of the poor data management. They are currently exploiting RPA in their work to improve productiveness. He/she says it could reduce the amount of monkey work like data transfers, which people do not want to do. This is in line with the business controller, who said above how he/she would happily to get rid of e.g. monthly closing.

> *'In addition to AI creating information, RPA can concretely make things and increase effectiveness and it is an area we have started to research and develop and we believe that in this kind of firm there are potential subjects although volumes are not as high as e.g. banks and network firms […]. People do not want to make these silly monkey work and data transfers and these kinds of things themselves so these are maybe the first areas where we will utilize machine learning.' – Business Unit Manager*

As a brief summary of this section, it seems that the data management in ManufacturingCo has serious problems. The issue hinders the thinking of possible AI benefits, as it the informants know the benefits are not possible to obtain before the data management is fixed. However, the AI needs listed in *Table 13* are realistic to implement with sufficient data. The business controller proposed a new intermediate role for him/her when managers work with AI. I will analyze and discuss this and other findings of this chapter more carefully in the next chapter.

5. SYNTHESIS OF FINDINGS AND DISCUSSION

I will answer the research questions in this chapter. The first section covers the **RQ1**: '*How does management accounting information initiate and influence decision-making processes?'.* The second section is about the ***RQ2***: '*What kinds of artificial intelligence (AI) needs emerge in managerial work?'* I answer the ***RQ3*** in the third section: *What kinds of boundary subjects are expected in decision-making with AI?*

In the first two sections, I use the cross-case analysis technique to illustrate patterns between cases, which increases the probability of novel findings (Eisenhardt 1989). As I mentioned in the previous chapter, I discussed the boundary subjects only in the ManufacturingCo section. Thus, I use the special case analysis method with *RQ3*. The sections include two types of elements, propositions and hypotheses. I gathered all the propositions and hypotheses in *Table 14.*

Table 14. *Propositions and Hypotheses*

Research Question	Type & Number	Title
RQ1	Proposition 1	In complex decisions, answer, ammunition, learning and rationalization machines (Burchell et al., 1980) are still present
	Proposition 2	New controller resource initiates financial planning re-engineering
	Proposition 3	Obtaining new market information initiates complex decision-making processes
	Proposition 4	The bigger the firm, the smaller the amount of converting guesses into data
	Hypothesis 4.1	Inflexible processes of big firms prevent converting guesses into data
	Hypothesis 4.2	The amount of converting guesses into data evolves as the company grows
RQ2	Proposition 5	Managers want market analyses, profitability tools and resource availabilities from AI
	Proposition 6	Managers see AI mostly as an answer machine (see Burchell et al., 1980)
	Hypothesis 6.1	Managers are not familiar with the other roles of accounting than answer machine (see Burchell et al., 1980)
	Proposition 7	Managers' AI needs are not entirely realistic
RQ3	Proposition 8	Firms should consider incorporating AI into their decision-making with the help of data accountant

I base the eight propositions of *Table 14* on the qualitative data of this thesis. The three working hypotheses are my own guesses on what the explanation for the particular proposition could be. This is in line with Silverman and Marvasti (2008, pp. 509) who define hypotheses as *'testable propositions often based on educated guesses'.* The paper of

Bourgeois and Eisenhardt (1988) inspired the structure of this chapter. Turning now to the first synthesis and discussion section.

5.1 Cross-case analyses on MA information initiating and influencing decision-making processes

Proposition 1. *In complex decisions, answer, ammunition, learning and rationalization machines (Burchell et al., 1980) are still present.*

Burchell et al. (1980) introduced us to four roles of accounting: answer, ammunition, learning and rationalization machines. I explained the meanings of the roles in section 2.3.1. The empirical evidence of their widely accepted framework is relatively thin despite the fact that it is almost 40 years old. Thus, I analyzed the four cases and found evidence on all of the four roles. I placed quotes from the informants to the framework and I present the results in *Table 15*. I labeled the quotes based on my interpretation of the whole case, and there is definitely room for debate in every quote whether its placement is correct or not. Next, I will go through four quotes, which cover all case firms and all roles, to give an example on how I formed the table.

Table 15. *Roles of MA information using Burchell et al.'s (1980) framework.*

	HardwareCo	AnalyticsCo	ProcessCo	ManufacturingCo
Answer machine	'When [the head of product] made the pricing calculations […] he believed the percentages are this and prices that and boom we got these numbers. And then we compared it [with the initial numbers].' – Product Development Director	'I am a very finance-oriented engineer. I always think that financial numbers have to be very well known, where we are, and they should be correct and reliable.' – Chair of the Board	'Because this is purely an investment project, some financial key indicators have to be calculated. […] first, the costs are estimated and therefore profit expectations, which lead to payback time and so on. Thus, [a presentation] is prepared for a "panel of judges" and then the plant management team decides if this is something that they want to invest in.' – Development Manager	'[…] people ask me [financial questions] and then I do analyses and interpret and explain them to people.' – Business Controller
Ammunition machine	'I would say mathematic calculation [is] just a one part. […] And [we] also need to compare [it] with […] their professional feeling about it.' – Controller	'The market share should be more than 15 % so it would be good enough. […] if it is not 15 % or 20 % then the market scope has to be reduced.' – Chair of the Board	'Projects might get on hold if the market situation or other plans change. […] If the portfolio seems to become too big and people start to fear that, for instance, there are not enough resources available, we start to go through the portfolio. Then some projects might get on hold or dismissed.' – Investment Controller	'If the goal is to improve profitability and the target setting is based on a conjecture that you cannot base anything on growth of the top line [of the P&L] so you cannot invest beforehand to increase fixed costs which meant that many optional investments had to be postponed and put on hold. […] And everyone will never be happy with that their favorite project does not move forward.' – Business unit manager
Learning machine	'The iteration process lead to that we found many miscalculations made by everyone including myself which improved the quality of the overall [budget].' – Product Development Director	(Not witnessed)	'[The most important thing that all the stakeholders should understand] is that this is purely a productivity investment so it does not necessarily bring any benefits to a single production area or a person […] but it is all about "common good" which improves the bottom line of the company.' – Development Manager	'Now that we have thought about these targets together and spent a lot of time on it at a management team level […] everyone is probably more committed to them [the targets]. Therefore, people at lower and lower level is much easier to make accountable for them as the numbers are accurate also at the top level or they have been created rationally.' – Business Controller
Rationalization machine	'We made together the number that went to the budget but [the procurement manager] said that he/she will still use his own number [for suppliers].' – Product Development Director	Even if we had all the information […] some people may still say, "Well here is the data but I had this meeting last week and the person said this damn thing! So that's it. A person believes what he wants to believe in a specific point of time."' – Co-founder, VP of sales & marketing	(Not witnessed)	(Not witnessed)

First, all of the roles seem to exist in *HardwareCo*. In my interpretation, this was the only case that has all of them based on the data. To pinpoint one example, the product development director stated that the procurement manager did not use the new budgeted production volume with the supplier. I argue this reveals that the decision-making process acted as a rationalization machine with some decision-makers, most likely with the product development director and/or the head of product.

AnalyticsCo has all the roles except the learning machine. The chair of the board says the market share should be at least 15 percent or the firm should change the scope. My interpretation is that the chair has used MA information (the market share number) to steer the company in a direction he/she desires.

The investment controller of *ProcessCo* states that everyone should understand that the particular productivity investment, which is rather uncommon for the company, is all about improving the profitability of the company, not about bringing benefits to an individual. I assume this means that many people have learnt this during the decision-making process, thus MA information had a learning machine role.

Finally, the business controller of *ManufacturingCo* says his/her job is to find answers to financial questions by making analyses and then interpreting and explaining them. Here I argue that MA information is not only an answer machine, but also a learning machine. Naturally, he/she gives some simple answers without further explanation, but the interpreting and explaining suggests that learning may happen as the controller links answers to operations.

Proposition 2. *New controller resource initiates financial planning re-engineering.*

An empirical study of Cobb et al. (1995) argue that a newly hired financial controller without banking experience partially initiated the changes in management accounting practices in a bank. The changes include budgeting process re-engineering. They also maintain that the increased number of qualified accountants affected the changes. Similarly, the cases of HardwareCo and ManufacturingCo included financial planning process re-engineering. In HardwareCo, one of the drivers for the re-engineering was that they had hired a new controller, who had enough time to recalculate their budget. Likewise, ManufacturingCo's did not use to have business controllers for every business unit, but they hired them. The new business controller of the studied business unit could not intuitively modify the budget of the last year, so he/she had to re-engineer the financial planning process as a whole. Thus, this proposition is based on evidence from both literature and the empirical cases of this thesis. The three cases contributing to this are from different industries, and the case of Cobb et al. (1995) is decades old, which improves the transferability. I double underlined the findings related to this proposition in *Table 16*, which illustrates the drivers for the decision-making processes in the cases of this thesis.

Table 16. *Drivers for decision-making processes.*

HardwareCo	AnalyticsCo	ProcessCo	ManufacturingCo
Recent market change in customer demand	Market research analysis	Recent market change in raw material prices	Inexperienced controller could not intuitively modify the budget of the last year
New controller resource	Noticing that already 60 % of the revenue comes from the new target market	Financial figures: costs, profits, payback period	*New controller resource*
Gut feeling that the production forecast is incorrect	First good reference in the target market		
Calculated forecast error of X million euros	Angel investment, product development loan		
	Troubles in sales		
	Realizing that the majority of the customers were Lean Six Sigma experts		
	Hiring new CEO and board members with experience in the new target market		

As seen in *Table 16*, there are many drivers for the decision-making processes. Goretzki and Messner (2016) state that future studies could *'examine how and why such changes to planning systems come about'*. Chenhall et al. (2013) call for research on how accounting practices are actually developed in organizations. The findings of HardwareCo and ManufacturingCo in answer directly to these requests.

Hall (2010) underlines that accounting information may initiate verbal conversations about problems. For example, the calculated forecast error of X million euros initiated discussions and decision-making in HardwareCo. This kind of accounting information is an example of being boundary object, and initiating conversations means knowledge integration and boundary work (see literature review summary in section 2.7). The data discussed above also supports the statement of Hall (2010) as new controller resource usually means that more accounting information becomes available, thus increasing the probability for initiating conversations.

Proposition 3. *Obtaining new market information initiates complex decision-making processes.*

Informants in three out of four cases (HardwareCo, AnalyticsCo and ProcessCo) said market information was initiating their complex decision-making processes. In HardwareCo, the recent change in customer demand was a key driver for their production forecast decision. Similarly, in ProcessCo, the recent market change in raw materials prices made the particular investment case to stand out from the project portfolio and sped up the decision-making process. AnalyticsCo bought a market research analysis and noticed that already 60 percent of the revenue comes from the new target market. However, market information did not initiate the fourth case, ManufacturingCo. I underlined these findings in *Table 16*, which represents the drivers for the decision-making processes. This proposition implies that at least the three case firms react to changes in their markets by initiating business decision-making processes.

Proposition 4. *The bigger the firm, the smaller the amount of converting guesses into data.*

Previous studies on firm size have previously revealed that structural inertia increases with firm size (cf. Hannah and Freeman, 1984; Audia and Greve, 2006). The paper of Audia and Greve (2006) also suggest that managers of large firms are more likely to take risks when performance is decreasing than they are in smaller firms. Saukkonen et al. (2018) propose that managers may not reflect taken-for-granted assumptions and Goretzki and Messner (2016) calls for research on how actors deal with uncertainty. Building on this discussion, I analyzed the cases based on the interpreted importance of MA information, perceived amount of converting guesses into data and the revenue of the firms. The results are shown in *Figure 6*.

Converting guesses into data means that the origin of guesses disappears, and people pass on subjective guesses as objective data. The interviews do not reveal this kind of action in AnalyticsCo. However, in HardwareCo the product development director accused the financial department of doing so. Thus, I interpret that the amount of converting guesses into data is high in HardwareCo.

> *'Sometimes it bothers me that they make really precise calculations in the Finance Department but do not think that it is based on nonsense. So, they convert gut feelings into data.' – Product Development Director*

The interpreted importance of MA information is my interpretation on how important MA information was for the case decisions. I argue that it was not important for AnalyticsCo as there were many non-financial drivers as seen in *Table 16.* In the other cases, I state the importance of MA information was high as all the mentioned drivers were financial except the new controller resource. I base the perceived amount of converting guesses into data on the opinions of the informants.

The business controller of ManufacturingCo argues that if probabilities from statistics are not considered during forecasting, your mood of the day may affect the targets. My interpretation is that he/she means that they are converting gut feelings into data to some extent, as someone has to come up with the probabilities. However, straight accusations did not emerge. I considered this by placing ManufacturingCo below HardwareCo in *Figure 6*.

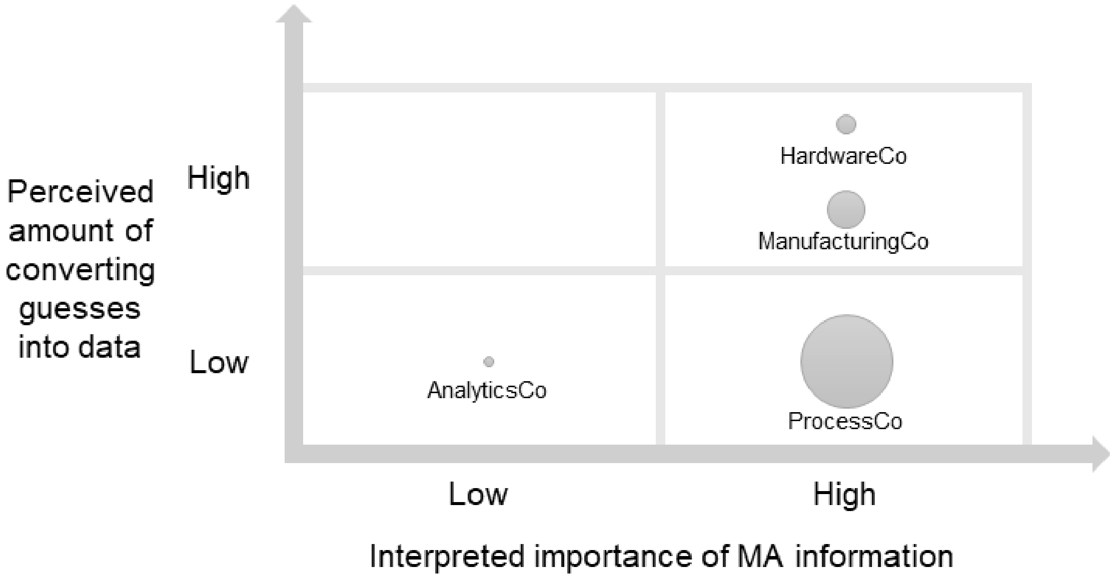

Figure 6. *Converting guesses into data and importance of MA information (size represents revenue).*

As seen on Figure 6, ProcessCo do not seem to convert guesses into data. The investment controller is responsible for maintaining their investment for Excel data sheet and investment instructions, which clearly set the rules on how the investments are calculated. Thus, there is little or no room for this kind of activity. Next, I will introduce you to two hypotheses based on this proposition.

Hypothesis 4.1. *Inflexible processes of big firms prevent converting guesses into data.*

As discussed in *Proposition 4*, ProcessCo has a relatively inflexible investment calculation process. In addition, the decision-making process is complicated as I explained in section 4.3.2. The investment controller states these may be required because the organization is so big and complex.

> *'Maybe it is required to have a heavy structure [behind this investment process] because the size and complexity of this organization. It could fall into a pitfall if information was passed by word of mouth.' – Investment Controller*

Thus, the inflexible processes i.e. structural inertia (cf. Hannah and Freeman, 1984) seem to protect the company from converting conjectures into data. My hypothesis here is that this idea could be transferable to other big firms, as the amount of inflexibility tends to be greater in big enterprises. The hypothesis is in line with the size and other characteristics of HardwareCo and ManufacturingCo as seen in *Figure 6*. This hypothesis should be tested with interviews in other large enterprises. This data set contains only one enterprise company and one decision; thus this topic needs more research. The findings of Audia and Greve (2006) in Japanese shipbuilding industry support this hypothesis by suggesting that the structural inertia is greater in larger companies than in smaller companies. Moreover, Saukkonen et al. (2018) revealed that fixed decision-making cycles of an enterprise delivery company decreased flexibility, which supports this hypothesis. The next hypothesis tries to explain why AnalyticsCo does not follow a linear pattern of decreasing amount of converting guesses into data.

Hypothesis 4.2. *The amount of converting guesses into data evolves as the company grows.*

If the companies of *Figure 6* are replaced with their size, we end up with a transferable version of the same figure. My hypothesis is that a growing company follows a pattern introduced in *Figure 7*. Micro-enterprises like AnalyticsCo struggle with their product-market fit, which means that they are still trying to find the right combination of products and customers. I argue that the importance of MA information is relatively low in this phase, because the profitability is expected to be negative. The amount of converting guesses into data is also low as the organization is very simple and there probably is not that much data available, so mixing the guesses and data is relatively hard.

As the micro-enterprise grows and finds its product-market fit, it becomes a small and medium-sized enterprise (SME). At this point, the processes of the company are still evolving, which means there are not clear procedures for everything. This gives room for converting guesses into data, and thus my hypothesis is that it is high among SMEs. HardwareCo and ManufacturingCo support this hypothesis. I suggest that in SMEs, MA information becomes more important, because the increasing revenue produces e.g.

cost-cutting opportunities, and the company starts to stabilize to fulfill the need it had discovered during the earlier phase.

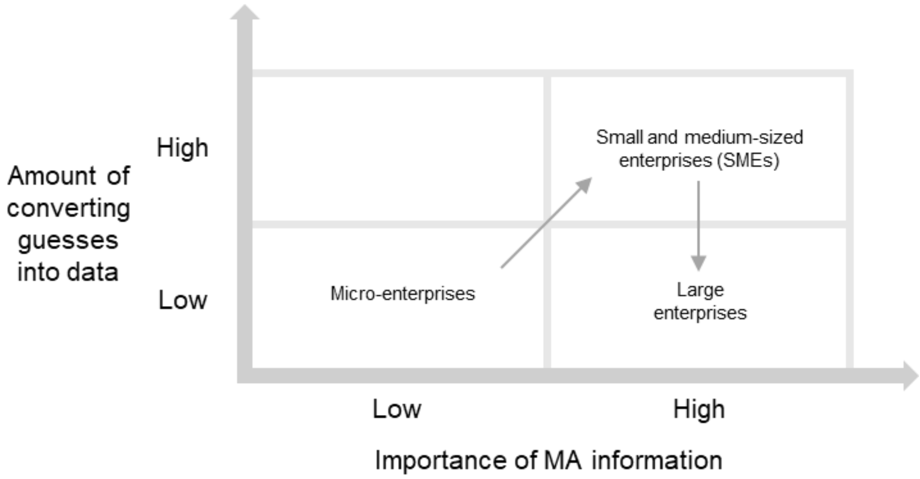

Figure 7. *Evolving amount of converting guesses into data from micro-enterprise to large enterprise (Hypothesis 4.2.).*

Finally, the importance of MA information in large enterprises is high. Otherwise, these companies would not have any controllers. My hypothesis suggests that the amount of converting guesses into data is low compared to SMEs. Inflexible processes may hinder reactiveness in market changes, but it may also hinder the amount of converting guesses into data. Centralized functions have well-defined process, which do not leave that much room for individually made guesses that are not well known. I base this hypothesis solely on the case data, and it does not consider enterprise life-cycle literature, which limits the transferability. Next, I will move on to cross-case analyses on the AI needs of the companies.

5.2 Cross-case analyses on AI needs

Proposition 5. *Managers want market analyses, profitability tools and resource availabilities from AI.*

A relatively old study of Marriott and Marriott (2000) revealed that small company owner-managers do not see accounting information as value for money. To continue the discussion in the modern era, we asked our informants what they would ask from AI regarding their work if it was possible to ask. Informants from three firms (HardwareCo, AnalyticsCo and ProcessCo) mentioned market information. This implies that these interviewees, and most likely their companies, need more market analyses. In HardwareCo, they would benefit from knowing when their customers start development programs. I argue that AI could deliver some information if an algorithm would comb through news on their customers' websites. I present selected AI needs of the four companies in *Table 17*, in which I underlined the market information needs with normal thickness.

Table 17. *AI needs in case companies*

HardwareCo	AnalyticsCo	ProcessCo	ManufacturingCo
Market analysis tool: competitive environment, behavior of existing and potential customers	Market analysis tool: market size, growth rate, competitors and key success factors in the industry	Market knowledge	What parameters affect sales margins?
What our leads are saying?	Market analysis tool: how many factories are there, how long is a typical buying process, what the customers want, head-to-head competitor product analysis	Sales tool	Which project will fail next?
Notification when our customer starts a development program		Neural network to improve profitability of the project portfolio	Profitability forecasts
Resource availability (components)		Resource availability (human, both internal and subcontractors')	What combinations of the offering are fatal to the supply chain?
Automated budgeting tool		Inventory turnover improvement	How much our costs increased last year?
Forecasting accuracy		Project prioritization	How much our procurement costs increased last year?
What are the most loved and most hated features of our products?		Visualization tool for project statuses and schedules	How much our prices increased last year?
Unusual use cases of our products		Resource shortages in projects How to manage projects more straightforwardly and efficiently	

Informants from ProcessCo and ManufacturingCo mentioned profitability tools during the interviews. The investment controller of ProcessCo would like to have neural network to improve their project portfolio. Unfortunately, we did not challenge this idea during the interview so it remains somewhat vague. The person seemed to have AI knowledge so the idea might have been reasonable. Similarly, the business unit manager of ManufacturingCo would like to have a profitability forecast tool and he/she would like to know which project fails next and what offering combinations are fatal to their supply chain. I argue that machine learning could fulfill these information needs if there was sufficient data available. I underlined the profitability-related needs with double thickness in *Table 17*. Managers would like to have more information on resource availability in two companies: In HardwareCo the interest lies with component availability and in ProcessCo with human resource availability both in their own organization and in subcontractors. I underlined these with dots in *Table 17*. This proposition contributes to the research gap revealed in section 2.7 as the proposed AI needs are also new boundary objects in decision-making with AI. In the next proposition, I will analyze the roles of AI with the framework of Burchell et al. (1980).

Proposition 6. *Managers see AI mostly as an answer machine (see Burchell et al., 1980).*

As I demonstrated in *Proposition 1*, all of the roles of Burchell et al. (1980) are still present in the cases. To continue this discussion, I analyzed the AI needs of the companies with the same framework. In majority of the AI needs, the informants see AI as an answer machine. This means that AI just gives answers to their questions. I show examples of this and the other machines in *Table 18*.

Table 18. *AI needs categorized in Burchell et al.'s (1980) framework.*

	ElectronicsCo	AnalyticsCo	EnergyCo	ManufacturingCo
Answer machine	'I would ask what the most-loved feature of my product is.' – Head of Product 'Budgeting could mostly be done with the help of AI. […] It could ask for certain inputs and then iterate it further.' – Product Development Director	'[I would ask AI] who are our competitors? – Chair of the Board '[I would ask AI] how long is a typical software buying process in [this] industry.' – Co-founder, VP of sales & marketing	'[I would ask AI] do we have enough resources [for a project]? And about the prioritization [of projects].' – Asset development team leader 'I would be interested in [AI solutions about] inventory turnover, sales and markets […].' – Investment Controller	'I think it would be really good if it [AI] would give straight answers. Now […] people ask me and then I make analyses and then interpret and go through them with people.' – Business Controller
Ammunition machine	'[I would ask AI] how accurately sales department have forecasted […] and of course my own accuracy. […] Is a big monthly deviation part of a trend or should it be ignored?' – Procurement Manager	(Not witnessed)	(Not witnessed)	(Not witnessed)
Learning machine	'[I would ask AI] how accurately sales department have forecasted […] and of course my own accuracy. […] Is a big monthly deviation part of a trend or should it be ignored?' – Procurement Manager	(Not witnessed)	'[I would ask AI] how to manage projects more straightforwardly and efficiently. In terms of scheduling, resourcing and costs. In addition, in this kind of plant.' – Development Manager	(Not witnessed)
Rationalization machine	(Not witnessed)	(Not witnessed)	(Not witnessed)	(Not witnessed)

In addition, I identified ammunition machine in HardwareCo, where the procurement manager would like to know how accurately the sales department forecasts sales. My interpretation is that he/she would use this information politically in their organization. However, he/she continues the same quote by saying that he would like to know his own accuracy as well. I argue that here AI is seen as a learning machine, because the person wants to learn how to make more accurate forecasts. Similarly, the development manager of ProcessCo would like know *'how to manage projects more straightforwardly and efficiently. In terms of scheduling, resourcing and costs. In addition, in this kind of plant.'* As he/she is responsible for those, I assume he/she would like to get better in his/her work with this information. Therefore, he/she sees AI as a learning machine. Last, I did not find rationalization machine in any of the cases. Next, I will introduce you to two hypothesis I created based on this proposition.

Hypothesis 6.1. *Most managers are not familiar with the other roles of accounting than answer machine (see Burchell et al., 1980).*

As I discussed in *Proposition 6*, most of the AI needs fell into the category of answer machine. I argue that this means the other roles of accounting (cf. Burchell et al., 1980) are not well known among managers. The case decision-making processes have characteristics from all the four roles as I suggested in *Proposition 1*. There is no evidence on why these other three roles would suddenly disappear when organizations implement AI in their complex decision-making processes. Thus, especially managers should be aware of all of these roles in order to promote healthy decision-making culture.

I state that the lack of knowledge has several organizational effects. First, ignoring ammunition and rationalization machines may lead up to extensive power on rhetorical devices over rational decision-making. For example, the case study of HardwareCo revealed that leaders should take extensive care of the motives of employees in order to avoid conflicts in MA innovations. In this case, the procurement manager was not convinced of the new jointly forecasted production volumes, as he/she felt personally responsible for them to the supplier. Thus, the outcome of the new budgeting process was two different production volumes: the official numbers for the budget and the procurement manager's unofficial numbers, of which the latter he/she communicated to the supplier. Second, if complex decision-making is not understood as a learning machine, it may hinder organizational learning, which may be more important than the decision itself. Next, I discuss how realistic the AI needs of the managers are.

Proposition 7. *Managers' AI needs are not entirely realistic.*

HardwareCo, AnalyticsCo and ProcessCo would like to have a general market analysis tool from AI. However, I argue that this is not realistic as there is not sufficient data available, and one can buy market analyses from consultants. Thus, solving this need with AI is not meaningful. Showing a resource availability status with AI, which I discussed in Proposition 5, is another example of an unreasonable AI need. If the data was available, I do not see how AI would make a difference to traditional software. Correspondingly, the above-mentioned resource availability seems to be anything but a meaningful AI need, as AI would not bring any additional value.

The examples above show that there are unrealistic expectations towards AI among managers. However, the discussion in *Proposition 5* show that some managerial needs are solvable with AI. I think this paradox could be solved by offering basic education on AI so the expectations among managers would be more realistic, which would bring AI closer to actually being in use. Next, I will move on to the special case analysis, which suggests a new decision-making process with a data accountant.

5.3 Special case analysis on boundary subjects in decision-making with AI

This section arises from the interview with the business controller of ManufacturingCo, who is highly skilled in both management accounting and data analytics. He/she would be 'completely satisfied' if AI could do e.g. monthly closing for him/her. However, he/she raises the question who would interpret and understand the AI analyses if they would have them available.

> *'But who would interpret and understand the [AI] analyses? I would be completely satisfied if there was AI that could do e.g. the monthly closing so that I would not have to. I could just take the ready-made data or figures like "it looks like this" and then analyze it further. So, I do not have anything against that AI would come and automate many tasks like those. But there has to be someone who understands what it produces.' – Business Controller*

Next, I will introduce you to my *Proposition 8,* which emerged from the discussion briefly explained above. I will expand the ideas of the business controller to a process. I will provide also a practical example and discuss a new role of data accountant. These contribute to the research gap introduced in section 2.7.

Proposition 8. *Firms should consider incorporating AI into their decision-making with the help of a data accountant.*

The literature review revealed that management accountants are becoming business partners (cf. Goretzki et al., 2013; Windeck et al., 2015) and thus boundary subjects. In addition, Moll and Yigitbasioglu (2019) state that accountants will be still needed for some traditional processes e.g. performance management. They also argue it is a duty of accountants to challenge the results that AI brings on the table and to take caution when someone uses the system as a black box without proper understanding. However, Richins et al. (2017) maintain that the tasks of the accounting function are most likely going through a change, which will bring new data-related opportunities for accountants.

I build on these viewpoints by introducing a new role of data accountant, which ties the management accountants, the business partner role, decision-making and AI together. A data accountant is a boundary subject, who has knowledge on both management accounting and data science. Therefore, the person is able to participate in decision-making as a business partner and to conduct advanced data analytics with AI.

The decision-making process with data accountant and AI goes as following. First, a decision-maker has a business problem. For example, a service manager would like to reduce warranty costs of their complicated industrial electronic products. Next, the decision-maker and data accountant have to form a more specific question or need, which can be asked from AI. This may be the hardest part of the process, as the question should be 1) relevant for the business problem, 2) solvable with AI and 3) there has to be sufficient data available. To continue the example, a specific question could be 'are there any correlations in the fault explanations written by customers?'. After the specific question has been formed, the data accountant stars a data science part. This includes usually many steps from data acquisition to data visualization, and it varies from case to case. I introduced one example in section 2.6.2 from Arnaboldi (2018). In this warranty cost example, the data accountant would use natural language processing (NLP) techniques. Next, the data accountant gets a specific answer with the help of AI. An example could be an array with the message 'there are 78 mentions of words "does not turn on" in this country'. Now, the answer has to be transformed into a possible solution to the business problem. The data accountant and the decision-maker make this interpreting together. In this case, the array reveals that warranty costs could be reduced, if every customer could turn their newly acquired products on. Better instructions and more training could solve this problem. After finding this out, the decision-maker acts and decides to start a new development program with a goal to improve the instructions and to create an online training program. I illustrate the whole process with the example in *Figure 8*.

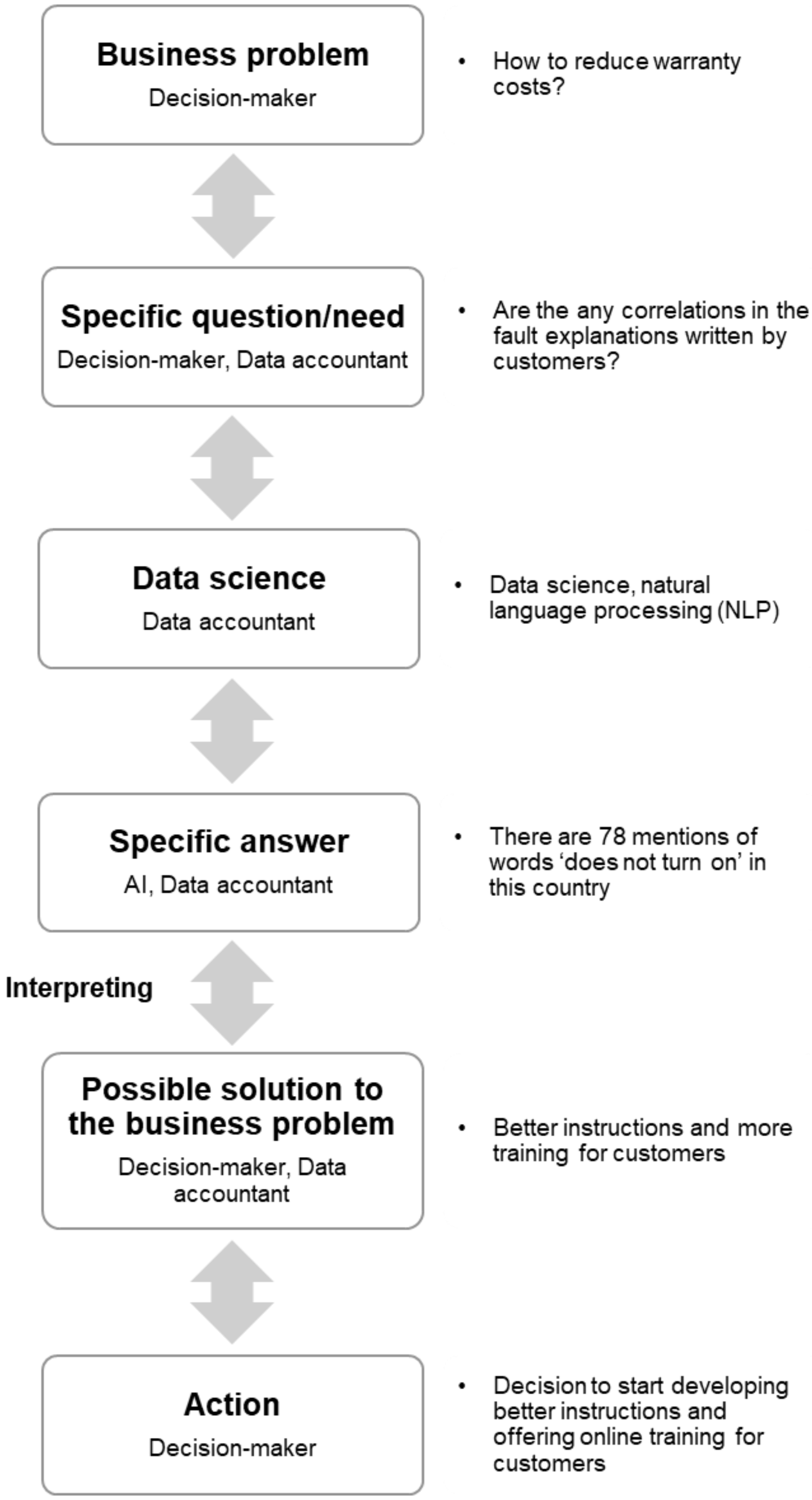

Figure 8. *Decision-making process with Data Accountant and AI (Proposition 8).*

In *Figure 8*, I have demonstrated how the proposed data accountant would act in decision-making processes with AI. This clearly contributes to the research gap (introduced in section 2.7), which suggests that decision-making with AI, especially in management accounting context, is almost completely unknown area among researchers. Now that I have lifted the veil of secrecy, I would like to point out that most of the research gap still remains, and there is plenty of room for different kinds of studies regarding this topic. Let us now conclude this thesis in the last chapter.

6. CONCLUSIONS

Despite the growing interest towards artificial intelligence (AI) research, management accounting (MA) research does not correspond in practice to the fact, that AI will affect decision-making processes in the future. In this thesis, I explored complex decision-making processes in four case companies with focus on the combination of management accounting, artificial intelligence and decision-making. The research questions are as follow:

> *RQ1.* How does management accounting information initiate and influence complex decision-making processes?
>
> *RQ2.* What kinds of artificial intelligence (AI) needs emerge in managerial work?
>
> *RQ3.* What kinds of boundary subjects are expected in decision-making with AI?

We conducted 11 semi-structured interviews to answer the questions. I used cross-case analysis (Eisenhardt 1989) technique to find patterns across the cases. Next, I will discuss my contributions to the research, limitations of the study and future research opportunities.

6.1 Contributions

This thesis provides 8 propositions and 3 hypotheses to management accounting, artificial intelligence and decision-making research. I introduced and discussed these in detail in *Chapter 5*. As I argued in *Section 2.7*, the specific combination of decision-making with AI has been neglected among researchers. For example, Granlund (2011) states that there is a need for both empirical and theoretical studies on the synthesis of accounting practices and modern IT.

As a key result, this thesis lifts the veil of secrecy on decision-making with AI. To demonstrate this, I illustrate the new decision-making process with AI in *Figure 9.* In addition, I have identified seven distinct contributions. First, *Propositions 2–3* state that new controller resource and obtaining market information are drivers for complex decision-making processes. Second, I argue in *Proposition 8* that a new role of *'data accountant'* should be established for incorporating AI into complex real-world decision-making processes. This proposition is in line with the ideas of Richins et al. (2017), who maintain that the tasks of the accounting function are most likely going through a change, which will bring new data-related opportunities for accountants. According to Moll and Yigitbasioglu (2019), accountants will be needed for some traditional processes e.g. performance management in the future. I argue that accountants will have a greater role – the proposed data accountant will act as a translator between AI solutions and managers. He/she translates the MA information needs of managers to AI and then explains the results and logic to the managers. This proposal emerged from an interview with the controller of ManufacturingCo, who is highly skilled in both machine learning and management accounting. Third, I propose a new AI process, which companies should follow with the Data Accountant. This idea is further explained in *Section 5.3*. Fourth, *Propositions 5–7* reveal that managers want market analyses, profitability tools and resource availabilities from AI, but the needs are not entirely realistic. The new decision-making process with AI and the four related contributions are shown in *Figure 9.*

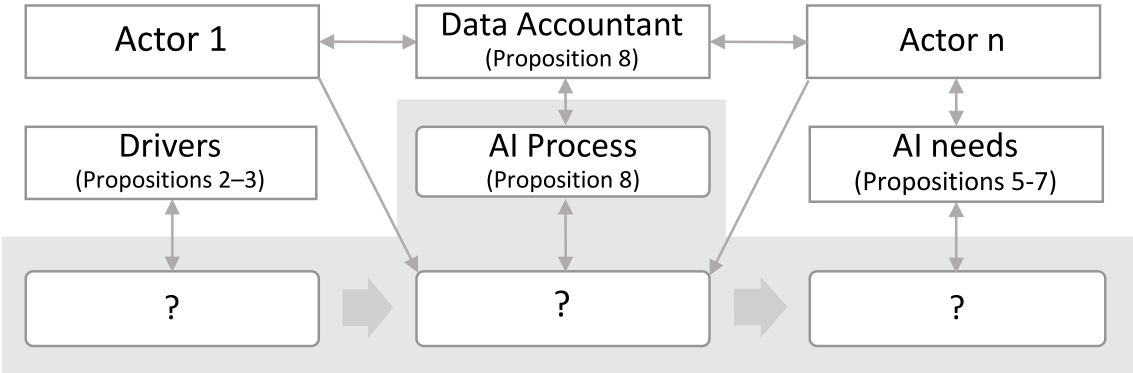

Figure 9. *Decision-making with AI and related contributions*

Figure 9 shows that there are still many question marks over decision-making with AI. To continue with the contributions outside of the figure, the fifth suggests that the majority of both managers and employees think AI would act only as an answer machine in decision-making. However, the results of this study *(Proposition 1*) imply that MA information also has the other roles of learning machine, ammunition machine and rationalization machine (roles introduced by Burchell et al., 1980) in decision-making. There is no evidence on why these other three roles would suddenly disappear when organizations implement AI in their complex decision-making processes. Thus, especially managers should be aware of all of these roles in order to promote healthy decision-making culture. Ignoring ammunition and rationalization machines may lead up to extensive power on rhetorical devices over rational decision-making.

Sixth, there seems to be lack of market information among senior managers and many informants saw AI as a solution to this problem. This provides an opportunity for either existing companies or startups to start offering an AI-based real-time market research tool. However, the needs could be fulfilled also with traditional market research, thus the true need for AI remains unknown. Seventh, the case study of HardwareCo revealed that leaders should take extensive care of the motives of employees in order to avoid conflicts in MA innovations. In this case, the procurement manager was not convinced of the new jointly forecasted production volumes, as he/she felt personally responsible for them to the supplier. Thus, the outcome of the new budgeting process was two different production volumes: the official numbers for the budget and the procurement manager's unofficial numbers, of which the latter he/she communicated to the supplier. Turning now to the limitations and future research opportunities.

6.2 Limitations and future research

Probably the most problematic limitation of this thesis is the lack of cases actually utilizing AI in decision-making. I considered this when the research questions were designed. To further judge the research design, I would like to add that I should have used quantitative methods for *RQ2* and *RQ3*, as they are 'what' questions. Yin (2003, pp. 6) suggests that this type of questions favor survey and archival strategies. Alternatively, I should have changed the research questions. Mixing the chosen case-study strategy with action or interventionist research methods would probably have provided results that are more comprehensive. That kind of research design could have partially captured informal communication, which happens during the decision-making processes.

This thesis was based only on interviews, which I could have supplemented by direct observation. However, it would have imposed a risk of being an over-complicated research design. If I would rewrite this thesis, I would make a two-case study of HardwareCo and ManufacturingCo. Those are somewhat similar cases, as they are about financial forecasting, which would offer an opportunity for *literal replication* (Yin, 2003, pp. 47). I did the data analysis manually, which means that some relevant information from the data is likely missing from this thesis. If I would have the chance to change something in the analysis, I would use software such as ATLAS.ti. Last, I would like to underline that some of the propositions and hypotheses are more reliable than others. For example, *Proposition 1*, which states that the roles of accounting are still present, is much more reliable than *Proposition 8*, in which a propose a new untested decision-making process.

Despite the limitations, this thesis lays the groundwork for future research by providing several contributions to the literature. Nevertheless, I have only lifted the veil of secrecy regarding decision-making with AI, and therefore future research is definitely required. It would be interesting to see comparative case studies between companies making decisions with and without AI. Possible research questions could be e.g. *'How decision-making with AI affect business performance?"*, *"How decisions are made with AI?" or "What is the perceived value of AI in decision-making among humans?"*. As a conclusion of the conclusions, I would like to remind you: Brace yourselves, AI is coming.

REFERENCES

Abernethy, M.A. and Brownell, P., 1999. The role of budgets in organizations facing strategic change: an exploratory study. Accounting, organizations and society, 24(3), pp.189-204.

Ahrens, T., 2018. Management controls that anchor other organizational practices. Contemporary Accounting Research, 35(1), pp.58-86.

Alqahtani, A. and Whyte, A., 2013. Artificial neural networks incorporating cost significant Items towards enhancing estimation for (life-cycle) costing of construction projects. Construction Economics and Building, 13(3), pp.51-64.

Arnaboldi, M., 2018. The Missing Variable in Big Data for Social Sciences: The Decision-Maker. Sustainability, 10(10), p.3415.

Arnaboldi, M., Azzone, G. and Sidorova, Y., 2017. Governing social media: the emergence of hybridised boundary objects. Accounting, Auditing & Accountability Journal, 30(4), pp.821-849.

Audia, P.G. and Greve, H.R., 2006. Less likely to fail: Low performance, firm size, and factory expansion in the shipbuilding industry. Management science, 52(1), pp.83-94.

Autor, D.H., Levy, F. and Murnane, R.J., 2003. The skill content of recent technological change: An empirical exploration. The Quarterly journal of economics, 118(4), pp.1279-1333.

Azambuja, R. and Islam, G., 2019. Working at the boundaries: Middle managerial work as a source of emancipation and alienation. Human Relations, 72(3), pp.534-564.

Baryannis, G., Validi, S., Dani, S. and Antoniou, G., 2019. Supply chain risk management and artificial intelligence: state of the art and future research directions. International Journal of Production Research, 57(7), pp.2179-2202.

Bhimani, A. and Willcocks, L., 2014. Digitisation, ‘Big Data’ and the transformation of accounting information. Accounting and Business Research, *44*(4), pp.469-490.

Bisbe, J. and Malagueño, R., 2015. How control systems influence product innovation processes: Examining the role of entrepreneurial orientation. Accounting and Business Research, 45(3), pp.356-386.

Bishop, S. and Waring, J., 2019. From boundary object to boundary subject; the role of the patient in coordination across complex systems of care during hospital discharge. Social Science & Medicine, 235.

Bourgeois, L.J. and Eisenhardt, K.M., 1988. Strategic decision processes in high velocity environments: Four cases in the microcomputer industry. Management science, 34(7), pp.816-835.

Briers, M. and Chua, W.F., 2001. The role of actor-networks and boundary objects in management accounting change: a field study of an implementation of activity-based costing. Accounting, organizations and society, 26(3), pp.237-269.

Burchell, S., Clubb, C., Hopwood, A., Hughes, J. and Nahapiet, J., 1980. The roles of accounting in organizations and society. Accounting, organizations and society, 5(1), pp.5-27.

Busco, C., Caglio, A. and Scapens, R.W., 2015. Management and accounting innovations: reflecting on what they are and why they are adopted. Journal of Management & Governance, 19(3), pp.495-524.

Busco, C. and Quattrone, P., 2015. Exploring how the balanced scorecard engages and unfolds: Articulating the visual power of accounting inscriptions. Contemporary Accounting Research, 32(3), pp.1236-1262.

Busco, C. and Quattrone, P., 2018. In Search of the “Perfect One”: How accounting as a maieutic machine sustains inventions through generative ‘in-tensions’. Management Accounting Research, 39, pp.1-16.

Camacho-Miñano, M.D.M., Segovia-Vargas, M.J. and Pascual-Ezama, D., 2015. Which characteristics predict the survival of insolvent firms? An SME reorganization prediction model. Journal of Small Business Management, 53(2), pp.340-354.

Carlile, P.R., 2002. A pragmatic view of knowledge and boundaries: Boundary objects in new product development. Organization science, 13(4), pp.442-455.

Cheng, M.Y., Wibowo, D.K., Prayogo, D. and Roy, A.F., 2015. Predicting productivity loss caused by change orders using the evolutionary fuzzy support vector machine inference model. Journal of Civil Engineering and Management, 21(7), pp.881-892.

Chenhall, R.H. and Euske, K.J., 2007. The role of management control systems in planned organizational change: An analysis of two organizations. Accounting, Organizations and Society, 32(7-8), pp.601-637.

Chenhall, R.H., Hall, M. and Smith, D., 2013. Performance measurement, modes of evaluation and the development of compromising accounts. Accounting, Organizations and Society, 38(4), pp.268-287.

Christensen, M. and Skærbæk, P., 2010. Consultancy outputs and the purification of accounting technologies. Accounting, Organizations and Society, 35(5), pp.524-545.

Cobb, I., Helliar, C. and Innes, J., 1995. Management accounting change in a bank. Management accounting research, 6(2), pp.155-175.

Cools, M., Stouthuysen, K. and Van den Abbeele, A., 2017. Management control for stimulating different types of creativity: The role of budgets. Journal of Management Accounting Research, 29(3), pp.1-21.

Coyte, R., 2019. Enabling management control systems, situated learning and intellectual capital development. Accounting, Auditing & Accountability Journal.

Cullen, J., Tsamenyi, M., Bernon, M. and Gorst, J., 2013. Reverse logistics in the UK retail sector: A case study of the role of management accounting in driving organisational change. Management Accounting Research, 24(3), pp.212-227.

Eisenhardt, K.M., 1989. Building theories from case study research. Academy of management review, 14(4), pp.532-550.

Englund, H. and Gerdin, J., 2015. Developing enabling performance measurement systems: on the interplay between numbers and operational knowledge. European Accounting Review, 24(2), pp.277-303.

Giovannoni, E. and Maraghini, M.P., 2013. The challenges of integrated performance measurement systems: Integrating mechanisms for integrated measures. Accounting, Auditing & Accountability Journal, 26(6), pp.978-1008.

Giovannoni, E. and Quarchioni, S., 2019. Exploring the generative power of performance measurement systems design. The British Accounting Review, 51(2), pp.211-225.

Goretzki, L. and Messner, M., 2016. Coordination under uncertainty: A sensemaking perspective on cross-functional planning meetings. Qualitative Research in Accounting & Management, 13(1), pp.92-126.

Goretzki, L., Strauss, E. and Weber, J., 2013. An institutional perspective on the changes in management accountants' professional role. Management Accounting Research, 24(1), pp.41-63.

Goretzki, L., Strauss, E. and Wiegmann, L., 2018. Exploring the roles of vernacular accounting systems in the development of "enabling" global accounting and control systems. Contemporary Accounting Research, 35(4), pp.1888-1916.

Grabski, S.V., Leech, S.A. and Schmidt, P.J., 2011. A review of ERP research: A future agenda for accounting information systems. Journal of information systems, 25(1), pp.37-78.

Granlund, M., 2011. Extending AIS research to management accounting and control issues: A research note. International Journal of Accounting Information Systems, 12(1), pp.3-19.

Gärtner, B. and Hiebl, M.R., 2017. Issues with Big Data. In The Routledge Companion to Accounting Information Systems (pp. 161-172). Routledge.

Hall, M., 2010. Accounting information and managerial work. Accounting, Organizations and Society, 35(3), pp.301-315.

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

Hannan, M.T. and Freeman, J., 1984. Structural inertia and organizational change. American sociological review, 49, pp.149-164.

Huzzard, T., Ahlberg, B.M. and Ekman, M., 2010. Constructing interorganizational collaboration: The action researcher as boundary subject. Action Research, 8(3), pp.293-314.

Ismail, N.A. and King, M., 2005. Firm performance and AIS alignment in Malaysian SMEs. International Journal of Accounting Information Systems, 6(4), pp.241-259.

Jönsson, S. and Lukka, K., 2006. There and back again: doing interventionist research in management accounting. Handbooks of management accounting research, 1, pp.373-397.

Jørgensen, B. and Messner, M., 2009. Management control in new product development: The dynamics of managing flexibility and efficiency. Journal of Management Accounting Research, 21(1), pp.99-124.

Kolbjørnsrud, V., Amico, R. and Thomas, R.J., 2017. Partnering with AI: how organizations can win over skeptical managers. Strategy & Leadership, 45(1), pp.37-43.

Korica, M., Nicolini, D. and Johnson, B., 2017. In search of 'managerial work': Past, present and future of an analytical category. International Journal of Management Reviews, 19(2), pp.151-174.

Kumar, V.N.S.A., Kumar, V., Brady, M., Garza-Reyes, J.A. and Simpson, M., 2017. Resolving forward-reverse logistics multi-period model using evolutionary algorithms. International Journal of Production Economics, 183, pp.458-469.

Laine, T., Korhonen, T. and Martinsuo, M., 2016a. Managing program impacts in new product development: An exploratory case study on overcoming uncertainties. International Journal of Project Management, 34(4), pp.717-733.

Laine, T., Korhonen, T., Suomala, P. and Rantamaa, A., 2016b. Boundary subjects and boundary objects in accounting fact construction and communication. Qualitative Research in Accounting & Management, 13(3), pp.303-329.

Laine, T., Paranko, J. and Suomala, P., 2012. Management accounting roles in supporting servitisation: implications for decision making at multiple levels. Managing Service Quality: An International Journal, 22(3), pp.212-232.

Latour, B., 2005. Reassembling the Social. An Introduction to Actor – Network Theory, Oxford University Press, Oxford.

Lukka, K. and Modell, S., 2010. Validation in interpretive management accounting research. Accounting, organizations and society, 35(4), pp.462-477.

Lukka, K. and Vinnari, E., 2014. Domain theory and method theory in management accounting research. Accounting, Auditing & Accountability Journal, 27(8), pp.1308-1338.

Loyer, J.L., Henriques, E., Fontul, M. and Wiseall, S., 2016. Comparison of Machine Learning methods applied to the estimation of manufacturing cost of jet engine components. International Journal of Production Economics, 178, pp.109-119.

Marriott, N. and Marriott, P., 2000. Professional accountants and the development of a management accounting service for the small firm: barriers and possibilities. Management accounting research, 11(4), pp.475-492.

Moll, J. and Yigitbasioglu, O., 2019. The role of internet-related technologies in shaping the work of accountants: New directions for accounting research. The British Accounting Review.

Mouritsen, J. and Kreiner, K., 2016. Accounting, decisions and promises. Accounting, Organizations and Society, 49, pp.21-31.

Nielsen, L.B., Mitchell, F. and Nørreklit, H., 2015, March. Management accounting and decision making: Two case studies of outsourcing. In Accounting Forum, 39(1), pp. 66-82). Taylor & Francis.

Nørreklit, H., Nørreklit, L. and Mitchell, F., 2010. Towards a paradigmatic foundation for accounting practice. Accounting, Auditing & Accountability Journal, 23(6), pp.733-758.

Parry, K., Cohen, M. and Bhattacharya, S., 2016. Rise of the machines: A critical consideration of automated leadership decision making in organizations. Group & Organization Management, 41(5), pp.571-594.

Payne, R., 2014. Discussion of 'Digitisation, 'Big Data' and the transformation of accounting information' by Alnoor Bhimani and Leslie Willcocks (2014). *Accounting and Business Research*, *44*(4), pp.491-495.

Petroutsatou, K., Georgopoulos, E., Lambropoulos, S. and Pantouvakis, J.P., 2012. Early cost estimating of road tunnel construction using neural networks. Journal of construction engineering and management, 138(6), pp.679-687.

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

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

Rikhardsson, P. and Yigitbasioglu, O., 2018. Business intelligence & analytics in management accounting research: Status and future focus. International Journal of Accounting Information Systems, 29, pp.37-58.

Rowe, C., Shields, M.D. and Birnberg, J.G., 2012. Hardening soft accounting information: Games for planning organizational change. Accounting, Organizations and Society, 37(4), pp.260-279.

Ruggeri, D. and Rizza, C., 2017. Accounting information system innovation in interfirm relationships. Journal of Management Control, 28(2), pp.203-225.

Saunders, M., Lewis, P. & Thornhill, A. 2016. Research methods for business students. 7th ed. Harlow: Pearson.

Saukkonen, N., Laine, T. and Suomala, P., 2018. Utilizing management accounting information for decision-making: Limitations stemming from the process structure and the actors involved. Qualitative Research in Accounting & Management, 15(2), pp.181-205.

Shehab, T. and Farooq, M., 2013. Neural network cost estimating model for utility rehabilitation projects. Engineering, Construction and Architectural Management, 20(2), pp.118-126.

Shrestha, Y.R., Ben-Menahem, S.M. and von Krogh, G., 2019. Organizational Decision-Making Structures in the Age of Artificial Intelligence. California Management Review, 61(4), pp.66-83.

Silverman, D. & Marvasti, A. 2008. Doing qualitative research: a comprehensive guide, SAGE Publications, Los Angeles (Calif.).

Spanò, R., Allini, A., Caldarelli, A. and Zampella, A., 2017. Controlling innovation and innovating control: insights from a knowledge intensive network. Business Process Management Journal, 23(6), pp.1359-1384.

Star, S.L., 1989. The structure of ill-structured solutions: Boundary objects and heterogeneous distributed problem solving. In Distributed artificial intelligence (pp. 37-54). Morgan Kaufmann.

Star, S.L., 2010. This is not a boundary object: Reflections on the origin of a concept. Science, Technology, & Human Values, 35(5), pp.601-617.

Star, S.L. and Griesemer, J.R., 1989. Institutional ecology, translations' and boundary objects: Amateurs and professionals in Berkeley's Museum of Vertebrate Zoology, 1907-39. Social studies of science, 19(3), pp.387-420.

Strathern, M., 2000. The tyranny of transparency. British educational research journal, 26(3), pp.309-321.

Sutton, S.G., Holt, M. and Arnold, V., 2016. “The reports of my death are greatly exaggerated”—Artificial intelligence research in accounting. International Journal of Accounting Information Systems, 22, pp.60-73.

Thomas, T.F., 2016. Motivating revisions of management accounting systems: An examination of organizational goals and accounting feedback. Accounting, Organizations and Society, 53, pp.1-16.

Tiitola, V., Jalonen, T., Korhonen, T. and Laine, T., 2019. Financial information and decision-making: examining possibilities and limitations for utilizing artificial intelligence in complex decisions. Tampere University, unpublished article, pp. 22.

Wiersma, E., 2009. For which purposes do managers use Balanced Scorecards?: An empirical study. Management accounting research, 20(4), pp.239-251.

Windeck, D., Weber, J. and Strauss, E., 2015. Enrolling managers to accept the business partner: the role of boundary objects. Journal of Management & Governance, 19(3), pp.617-653.

Wouters, M. and Kirchberger, M.A., 2015. Customer value propositions as interorganizational management accounting to support customer collaboration. Industrial Marketing Management, 46, pp.54-67.

Wouters, M. and Roijmans, D., 2011. Using prototypes to induce experimentation and knowledge integration in the development of enabling accounting information. Contemporary Accounting Research, 28(2), pp.708-736.

Yin, R. K. 2003. Case study research: design and methods. Sage Publications, Thousand Oaks, 3rd ed.

APPENDIX A: INTERVIEW GUIDE

1. **Background & your story (~30 min)**
   a. Introduction (name, title, background, experience in the company)
   b. Story of the decision-making process
   c. Why did you choose this decision? [if applicable]
   d. What were the critical steps in this decision-making process?
2. **Defining the unit of analysis and the decision-making/control/objectives (~30 min)**
   a. How big or small this decision was for the company?
   b. How complicated it was? Why?
   c. How transparent or understandable it was?
   d. Who participated in it? Who are responsible for it?
   e. What kinds of impacts are you looking for with this decision?
   f. Who can affect the results? How?
   g. How do you make sure that these impacts are achieved? [before and after]
   h. What would you like to improve regarding this decision?
3. **Facts & feelings: facts, intuition and the need for financial information (~20 min)**
   a. What are the essential things that people should understand about this decision?
   b. Were there any disagreements or other challenges?
   c. Did you use any financial information?
   d. What did you do if needed information was not available?
4. **Engaging interactions: Especially actor's perspective (~20 min)**
   a. What kind of important information is needed for the decision-making?
   b. What is important for yourself in this decision? What kinds of values do you have?
   c. What things did everyone agree?
   d. What things needed discussions?
   e. What kinds of communication channels did you use?
5. **Accounting information supporting managerial work: the provision of financial information (~20 min)**
   a. What would you ask from AI if it was possible?
   b. Would you use that information?
   c. What should be done [in your company] in order to be able to ask those questions from AI?