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INTEGRATING ANALYTICS WITH ENTERPRISE INFORMATION SYSTEMS

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BY
CLAUS BOYE ASMUSSEN

DISSERTATION SUBMITTED 2021

AALBORG UNIVERSITY
DENMARK

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CV

Claus Boye Asmussen was born on the 12th of May 1987 in Guderup, Denmark. He completed a BSc degree in Global Business Engineering in 2010 and an MSc in Operations and Supply Chain Management in 2012 at Aalborg University. Afterwards, he worked as an SAP Sales and Distribution specialist at the pharmaceutical company Lundbeck in Copenhagen from 2012 to 2014. Thereafter, he simultaneously joined as an SAP consultant at the management consulting firm Syncronic and as a part of the sales forecasting start-up company Sophub from 2014 to 2018. His main responsibilities within SAP consulting were in the areas of sales and distribution, master data, and advanced planning. His responsibilities within Sophub were to co-design and construct a cloud-based sales forecasting solution primarily using time series analysis techniques and to manage daily operations and participate in sales meetings with clients from different industries. He has experience in several industries, mainly retail, pharmaceutical and food and beverages. He started as a PhD student at Aalborg University in 2018, where his research in integrating analytics with Enterprise Information Systems and Operation and Supply Chain Companies is part of the Manufacturing Academy of Denmark, which is funded by the Innovation Fund of Denmark.

ENGLISH SUMMARY

Technological progress over recent decades has enabled Operations and Supply Chain (O&SCM) companies to record, manage and process data through analytics into valuable insights and actions. The insights and actions have proved to enable O&SCM companies to outcompete competitors, where several reports have shown superior overall company performance when having successfully integrated analytics into their business processes. Naturally, this has attracted the attention of both practitioners and academics. However, these results have been difficult to replicate. Researchers have first addressed the issue by trying to define the concept of value for analytics, Enterprise Information Systems (EIS), (big) data, and O&SCM. While there is no explicitly accepted definition of value, there is still a consensus on the overall aspects of the definition of value. However, the underlying value mechanisms have not been researched, and thus, it is largely unknown how to create value by integrating analytics with EIS for the O&SCM company. Thus, the aim of this thesis has been to research the value mechanisms within the research themes of analytics, EIS and O&SCM. Additionally, one of the main motivations for the PhD thesis is to narrow the gap from practice to promise, which entails that practical and academic relevancy is seen as equally important. Consequently, the research of this thesis has a strong practical outlook.

The research of the thesis uses a Design Science Research (DSR) approach, based on the foundation of the knowledge base, as well as constructing and deploying analytical artifacts into real environments. The PhD thesis is conducted as a part of the Manufacturing Academy of Denmark (MADE) programme. The construction and deployment of analytical IT artifacts have been conducted at the Danish dairy company Arla Foods.

The research of the thesis is based upon a structured literature review, action design science research, where analytical artifacts were construed and deployed at Arla Foods, as well as a review of the knowledge base. The outcome of the research is several identified value mechanisms and critical success factors (CSF), which have been combined with the research themes of analytics value theory, IT business value theory, and O&SCM theory into a value framework. The value framework presents an overview of the value mechanisms for different stages of the creation of value and analytical process, based on the use of the CRISP-DM framework. Further, the value framework introduces the concept of an analytical decoupling point, which aids in managing explorative and exploitive analytical processes.

To evaluate the value framework in a naturalistic environment and to make the research easier to communicate to a managerial audience, was the value framework

instantiated. The value framework was first instantiated into an approach, which was further instantiated into an explorative, exploitive and ambidextrous framework. The instantiations aid in understanding how the value framework can be used but are limited by the author's knowledge within the research themes, and thus the instantiations cannot be seen as generalisable. Finally, to evaluate the value framework is the ambidextrous framework instantiated as two demonstrators at Arla Foods: a demand planning and manufacturing case.

This thesis serves as a starting point for understanding the underlying value mechanisms of integrating analytics with EIS for the O&SCM company. Additionally, the thesis extends the understanding of value by combining the research areas of EIS, analytics, O&SCM, analytics value theory, and IT business value theory. The thesis also contributes to the concept of an analytic decoupling point, which can be used to manage explorative and exploitive analytical processes. The value framework can for researchers be used as an outset for further research within the research field. Research is recommended to be within the themes of how to identify analytical, IT and data management capabilities, data barriers, evaluating the value framework in more environments, research analytic decoupling points, and researching self-service analytics. For practitioners, the research is highly relevant, as it identifies and presents value mechanisms, as well as shows how the value mechanisms can be used in a real environment. Further, five recommendations are presented for the managerial audience: separate analytics and business process management (BPM), build cross-functional capable teams, democratise data science, make use of the analytic decoupling point, and use state-of-the-art open-source software.

DANSK RESUME

Den teknologiske udvikling over de sidste årtier har for Operations and Supply Chain (O&SCM) virksomheder gjort det muligt at registrere, håndtere, samt processere data til værdifuld indsigt og handlinger. Disse indsigter og handlinger har været brugt til at udkonkurrere konkurrenter for O&SCM-virksomheder, hvor flere rapporter har vist at virksomheder bliver mere konkurrencedygtige når de succesfuldt integrere brugen af analytics i virksomhedens processer. Dette har naturligvis, haft en interesse fra både den akademiske og praktiske verden. Resultaterne har dog været svære at replikere. Forskere har i første omgang håndteret denne problemstilling ved at forsøge at definere konceptet værdi inden for temaerne analytics, Enterprise Information Systems (EIS), (big) data, og O&SCM. Selvom der ikke eksplicit er en officiel accepteret definition of værdi, er der overordnet set en general konsensus omkring de overordnede aspekter af definitionen på værdi. Dog, har de underliggende værdi mekanismer ikke været undersøgt og det er derfor stort set uklart hvordan at værdi bliver skabt ved at integrere brugen af analytics i EIS for O&SCM-virksomheden. Derfor er målet for denne afhandling at undersøge værdimekanismerne inden for temaerne af analytics, EIS, og O&SCM. Derudover, har det været en motivation for afhandlingen at indsnævre gabet mellem forskningen og virkeligheden, hvilket betyder at det akademiske og praktiske bidrag er set som lige relevante. Som konsekvens af dette har afhandlingen et stærkt fokus på praktikalitet.

Forskningen i denne afhandling gør brug af Design Science Research (DSR), som er baseret på brugen af den tilgængelige vidensbase, samt baseret på konstruktionen og integrationen af analytiske artefakter i virkelige miljøer. Denne Ph.d.-afhandling er en del af Manufacturing Academy of Denmark. Konstruktionen og integrationen af analytiske IT-artefakter har været foretaget ved den danske mejerivirksomhed Arla Foods.

Forskningen i denne afhandling er baseret på et struktureret litteratur review, action design science, hvor analytiske artefakter er konstrueret og integreret i Arla Foods, samt ved at gennemsøge vidensbasen. Resultatet af denne afhandling er flere identificeret værdi mekanismer, samt Critical Success Factors (CSF), hvilket har været kombineret med forskningstemaerne analytisk værdi teori, forretning IT-værdi teori, samt O&SCM-teori til et værdiframework. Værdiframeworket præsenterer en oversigt over værdimekanismerne og hvordan de skal bruges i forskellige stadier i skabelsen af værdi samt i de analytiske processer, som er baseret på brugen af CRISP-DM frameworket. Frameworket præsenterer yderligere konceptet omkring det analytiske afkoblingspunkt, som hjælper med at håndtere den eksplorative og udnyttende analytiske processer.

Evalueringen af værdiframeworket er sket ved at instantiere værdiframeworket i et naturalistisk miljø, hvor forskningen er nemmere af kommunikere til at ledelsesmæssigt publikum. Værdiframeworket blev først instantieret til en tilgang, som yderligere blev instantieret til et explorativt, udnyttende, samt et ambidesktralt framework. Instantieringerne hjælper med at forstå hvordan værdiframeworket skal anvendes, men fordi det er begrænset af forfatterens viden inden for forskningstemaerne, kan instantieringerne ikke ses som generaliserbare. Til sidst, er det ambidesktrale framework instantieret i to demonstratorer ved Arla Foods, i hhv. en salgsplanlægnings og produktions case.

Afhandlingen kan ses som et udgangspunkt for at forstå værdimekanismerne ved at integrere analytics i EIS for O&SCM-virksomheder. Derudover udvider afhandlingen forståelsen af værdi, ved at kombinere forskningstemaerne analytics, EIS, og O&SCM, med analytisk værdi teori, samt IT-forretnings værdi teori. Afhandlingen bidrager derudover med konceptet omkring et analytisk afkoblingspunkt, som kan bruges til at håndtere de eksplorative og udnyttende analytiske processer. For forskere kan værdiframeworket bruges som et udgangspunkt for yderligere forsknings inden for området. Det anbefales at lave yderligere forskning inden for områderne: hvordan identificeres IT, data, samt analytiske kapabiliteter, data barriere, evaluering af værdiframeworket i flere miljøer, forsk i det analytiske afkoblingspunkt, samt forske i self-service analytics. Forskningen i denne afhandling er derudover yderst relevant for et ledelsesmæssigt publikum, da forskningen viser mekanismerne for hvordan værdi skabes, samt viser hvordan disse kan anvendes i et virkeligt miljø. Fem anbefalinger er identificeret for værdiskabelse for virksomheder, de er: adskil de analytiske processer og BPM, opbyg tværfunktionelle hold, demokratiser data science, gør brug af det analytiske afkoblingspunkt, samt gør brug af open-source software.

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The completion of this PhD thesis has been a long and joyful journey, where I have not only had great learning experiences, but have also had the opportunity to work and share moments with colleagues and industrial partners, for which I am very grateful. These experiences have developed me academically, professionally and personally. I can clearly state that I am a better person after having finished my PhD, which would not have been possible without your support.

First, I would like to thank my lovely wife Christine, who enabled and convinced me to join the PhD programme and has provided invaluable support throughout this journey. Your support and love have meant the world to me, which have proven to be invaluable throughout this journey. Together with our daughter Astrid, have you provided me with a happy home, which never fails to lift my spirit.

I would also like to express my gratitude to my supervisor Charles Møller, who has been a vital part in learning the academic craft. Before joining the PhD programme, I had a practical view on research, and you provided me with perspectives and tools for finding the balance in research that contributes to both theory and practice.

Further, I had the pleasure of working with too many people at Arla Foods to mention each one in this section, but I would like to thank them all. I would like to specifically thank Steffen Lundgaard Jørgensen and Søren Bækgaard Hansen, who were an incremental part of the success of this thesis. Steffen and I spent countless hours during the last three years brainstorming, designing, building, doing stakeholder management, identifying relevant use cases, and much more, which I am more than grateful for. I hope we can continue with this great partnership in the future. Søren has been invaluable in keeping the project on track and opening doors within the Arla Foods organisation.

I am very thankful for the inspiration and work of my colleagues at the Department of Materials and Production at Aalborg University, where, while I may only have been a weekly visitor, you always managed to make me feel like an equal part of the group.

Thanks to you all.

Claus Boye Asmussen

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Article 1. Asmussen, Claus Boye, and Charles Møller. 2019. “Smart Literature Review: A Practical Topic Modelling Approach to Do Exploratory Literature Review.” *Journal of Big Data*, no. 6: 93. doi:https://doi.org/10.1186/s40537-019-0255-7

Article 2. Asmussen, Claus Boye, and Charles Møller. 2020. “Enabling Supply Chain Analytics for Enterprise Information Systems: A Topic Modelling Literature Review.” Journal of Enterprise Information Systems 14 (5). Taylor & Francis: 563–601. https://doi.org/10.1080/17517575.2020.1734240.

Article 3. Asmussen, Claus Boye, Steffen Lundgaard Jørgensen, and Charles Møller. 2020. “Design and Deployment of an Analytic Artifact – Investigating Mechanisms for Integrating Analytics and MES.” Journal of Enterprise Information Systems, In 2. Review.

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Chapter 1. Introduction

Managing a company in today’s competitive environment is becoming increasingly difficult, as the complexity and uncertainties of managing operations and supply chain companies (O&SCM) continue to rise as a result of the increasing data flows introduced to the O&SCM companies (Beer 2018; Bose 2009). Companies are required to process the increasing data flow to generate insights and actions, enabling the company to make better and faster decisions. The successful processing of enterprise data into insights and actions will generate better O&SCM execution and planning outcomes, and consequently create value and increase competitiveness for a company (Davenport and Harris 2007; Hazen et al. 2014; Herden 2019). As such, the use of analytics for increased value creation has attracted significant industrial and academic interest fuelled by reports about superior company performance (Banerjee, Bandyopadhyay, and Acharya 2013; Barbosa et al. 2017; Davenport and Harris 2017; McAfee and Brynjolfsson 2012; Zhong et al. 2016). However, the value generated from analytics has been difficult to replicate for other companies, despite efforts to understand the mechanisms of value creation, and accordingly, academics and practitioners are uncertain on how value is created from analytics (Barbosa et al. 2017; Sanders 2016; Schoenherr and Speier-Pero 2015; Viaene and Van Den Bunder 2011; Zhu and Kraemer 2005). An industry report (Thieullent et al. 2016) also shows that only 18 percent of companies have deployed analytics initiatives across operations and achieved the desired objective. They compare the ‘gamechangers’ with the ‘laggards’ and find that gamechangers have better integration and higher utilisation of operational data. Further, Appelbaum et al. (2017), Hahn and Packowski (2015), and Ishaya and Folarin (2012) report that many companies are still at a low analytical maturity level and make use only of descriptive and diagnostic analytics.

One of the most cited and used analytic value models is proposed by Gartner in *Figure 1*. The model proposes a correlation between the difficulty of the analytical method used, ranging from descriptive, diagnostic, predictive, to prescriptive analytics, and the amount of value created. However, it has been difficult to verify the correlation between value and difficulty, and the model lacks guidance in how companies can specifically create value from analytics.

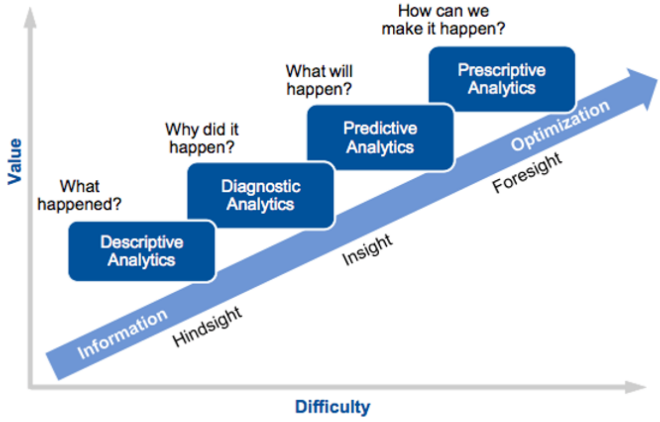

Figure 1. Analytics value escalator (Gartner 2012a).

Consequently, there is a need to gain an understanding of what mechanisms are needed to generate value for the O&SCM company by the use of analytics, which is the overall focus of this thesis.

This PhD dissertation is a part of the Manufacturing Academy of Denmark (MADE) programme where this specific thesis was done in cooperation with the Danish dairy company Arla Foods, and as a result has a strong focus on practicality and relevance for industry, while making sure the rigor of research is at a PhD level. The research addresses general issues faced by the industry but is developed and constructed in the context of Arla Foods. Arla Foods is a large dairy company with roughly 19,000 employees that grossed 10.5 billion euros in 2019 (Arla Foods 2020). Arla Foods produces milk, cheeses, yogurt and other dairy products and is structured as a cooperative owned by the farmers.

The approach of the thesis is to build demonstrators and IT artifacts in a design science methodology to identify mechanisms and gain an understanding of the phenomenon in integrating analytics with Enterprise Information Systems (EIS). The dissertation is motivated by a desire to close the gap between practice and promise, i.e. bridging the gap between research and practice as identified by Jonsson and Holmström (2016).

1.1 Structure of the thesis

This section describes the structure of the thesis, presented in *Figure 2*.

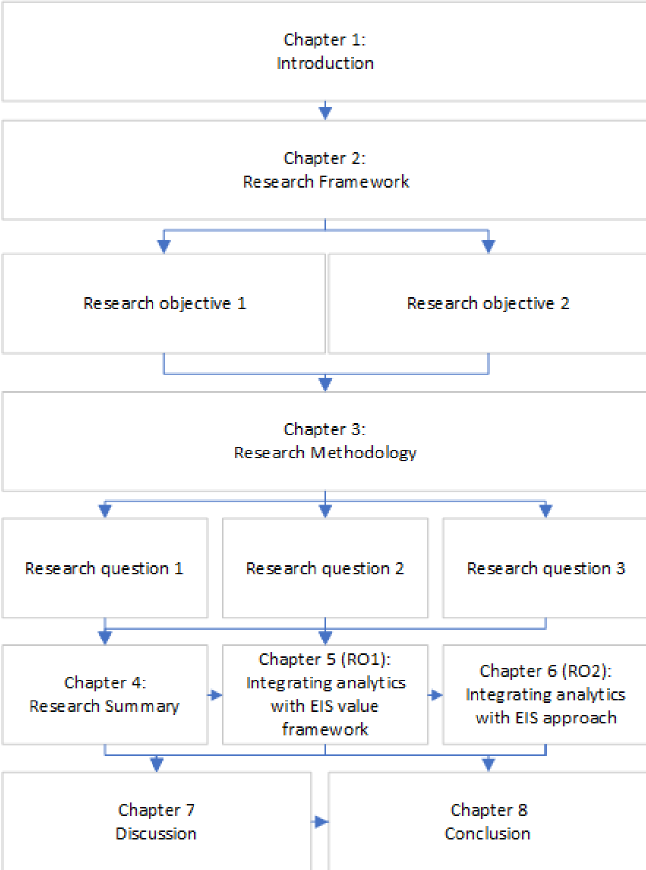

Figure 2. Structure of the thesis.

The thesis has a total of eight chapters, which are now sequentially described. The first chapter introduces the overall problem and research themes of the thesis. The second chapter discusses and presents a research framework that scopes the research by first discussing how value is understood in this research context. Next, the three research themes of Operations and Supply Chain Management (O&SCM), analytics and EIS are presented and described. The final part of the chapter discusses the relevancy and purpose of the thesis, which is concluded by presenting the research objectives.

The third chapter presents the research design and methodology. The chapter includes discussions on research philosophy, research forms, and the use of Design Science Research (DSR). The discussion on DSR has a special focus on ensuring both practical and academic relevance and rigor. Finally, the research methodology is presented, which proposes three research questions aiding in addressing the research objectives.

The fourth chapter summarises the research of the attached papers and effectively addresses the three research questions. First, a summary of the papers is presented. Next, the findings and conclusions of the summaries are synthesised according to being observed in the knowledge base, in a real-world environment, or observed in both cases. The synthesised summary presents an overview of the identified mechanisms of integrating analytics with EIS. The synthesised summary is further processed into operational critical success factors (CSF) for integrating analytics with EIS.

The fifth chapter presents a value framework that improves and extends the understanding of value within the research themes of analytics, EIS and O&SCM. Additionally, the value framework defines *how* value can be created by the use of the identified mechanisms. The value framework is constructed using DSR, which is based on the foundation of the research presented in chapter 4 and by exploring the academic knowledge base on the research themes of big data SCM value framework, IT business value theory, analytics value theory, and O&SCM theory. The value framework is constructed based on value discovery, analytic value intersection, and value creation as defined by Brinch (2018) and by the use of the analytic process framework CRISP-DM (Shearer 2000). The framework addresses the issue of balancing the exploratory and exploitive processes by relating it to a decoupling point and the identified value mechanisms, CSF and IT capabilities. It is believed that the framework brings clarity for the creation of value in the research themes of analytics, EIS and O&SCM for both academics and practitioners.

The sixth chapter presents an approach that instantiates the presented value framework, using currently available technologies and methods. The reason for creating an approach and instantiating the value framework is twofold. First, the creation of an approach is seen as a way to close the gap between practice and promise, as to create an understanding of how to transform the presented mechanisms into a practical approach. Second, the value framework is evaluated by the use of the approach by two demonstrators, where the value framework is evaluated in a real-world environment. Consequently, the chapter will present how the value framework is transformed into an approach and describe the issues of doing so with the currently available technologies and methods. Additionally, there are three instantiations presented as frameworks for an exploratory, exploitive and ambidextrous approach. The ambidextrous framework is used to construct two demonstrators in a demand planning and manufacturing case, respectively.

The last two chapters discuss and conclude the thesis. The methodology of the thesis is discussed, as well as the managerial and academic implications of this thesis, presenting the limitations of the research and suggestions for future research. Finally, the thesis is concluded by answering the research objective and summarising the research of the thesis.

Chapter 2. Research framework

The purpose of this section is to frame the research scope of the thesis in the form of a research framework and conclude by presenting the thesis research objectives. The section first presents a discussion and definition of value within the research themes of analytics, EIS and O&SCM. Next, the research themes are presented and summarised in the following order: O&SCM, analytics and EIS.

Next, the relevance and purpose of the thesis are discussed, and the research framework is finally presented. The chapter concludes by presenting the research objectives of the thesis.

2.1. Value generation by analytics for O&SCM

Managing a company has changed significantly over the recent decades, where the development of technology has enabled new and more complex ways of dealing with the uncertainties faced by companies today. The introduction of technologies such as the internet of things (IoT) and cloud computing have enabled companies to generate, record, store and process ever-rising volumes of enterprise data and convert the data into insights and actions (Beer 2018; Bose 2009). These insights and actions can improve operations and supply chain execution and planning processes, such as improving inventory management and making production scheduling and demand planning more accurate. Further, the use of analytics can incorporate complex factors to include aspects such as the interrelationships between market and company in a faster, more precise, and accurate way (Herden 2019; Holsapple, Lee-Post, and Pakath 2014; Kiron, Prentice, and Ferguson 2014; Kiron et al. 2011; Marchand and Peppard 2013). Company processes are also becoming increasingly data dependent, as the use of data and analytics is seen as an instrumental way of achieving better firm- and process-level performance (McAfee and Brynjolfsson 2012; Ramanathan et al. 2017). The increased use of data is now seen as a competitive prerequisite, as having up-to-date information is essential for supply chain execution and planning (Gunasekaran and Ngai 2004), and not having meaningful information can be seen as a risk to the company (Kache and Seuring 2017). As a consequence, it is generally accepted that the use of enterprise data is highly important for a competitive O&SCM company (Arunachalam, Kumar, and Kawalek 2017; Asmussen and Møller 2020; Brinch 2018; Brinch et al. 2018; Hult, Slater, and Ketchen 2004; Kache and Seuring 2017; Lavalle et al. 2011; Nguyen et al. 2017; Ross, Beath, and Quaadrgrass 2013; Zhong et al. 2017).

2.1.1. Defining value

The use of enterprise data is essential for modern-day companies to generate value that can make them more competitive. However, before addressing how value can be generated, value must first be defined in the context of O&SCM, which is the aim of this section.

The management of O&SCM companies is done through business processes, which is often managed by employing business process management (BPM) practices, which essentially analyses, designs, develops and executes business processes with the aim of optimisation, while ensuring the interaction and control of the processes (de Morais et al. 2014). The goal is to improve the effectiveness and efficiency of the company processes, i.e. improving the control, execution and planning processes. A company can achieve higher *effectiveness* by introducing innovations and process redesigns and by *exploring* the use of company resources in new ways (Brinch 2018). To increase the *efficiency* of the company's processes, the company must *exploit* its resources continuously to better manage and improve the output of the processes (Brinch 2018). In essence, companies need to decide between exploring the use of enterprise data to change the current company processes to do things in new ways or to exploit the enterprise data to become more efficient in the use of current resources by increasing the output of the individual process.

Based on the definitions above, Brinch (2018) proposes a framework which defines three types of value generated from O&SCM business processes from an IT business process perspective, depicted in *Figure 3*.

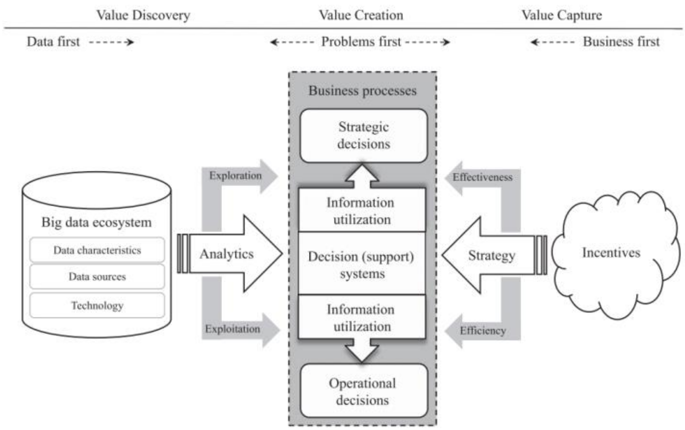

Figure 3. O&SCM data and analytics value framework (Brinch 2018).

Based on the framework, value can be understood from three perspectives:

- **Value discovery** – Manage data to ensure a transparent processing of data which can stem from a complex network of systems and data sources and technologies processed by analytics.
- **Value creation** – The use of data for better decision-making for a business-specific problem, generally by the use of EIS and decision support systems.
- **Value capture** – Capturing value by the use of data in economic terms or competitive gains, based on the activities in value discovery and value creation aligned with the strategic goals of the company.

Central to the value definitions is that business processes are at the heart of the creation of value from enterprise data. On the one hand, value can be discovered by the use of analytics to identify and create value for better management of the business processes, i.e. planning, control and execution. On the other hand, value can be created by adopting strategic innovation initiatives through the exploration of data. The viewpoint on value is significantly different between the three perspectives, where only value capture can be measured by traditional financial terms. Measuring value discovery and value creation is more difficult, as they rely on subjective terms such as perceived improved decision-making or improvement in business processes based on new or better insights or actions extracted from data. For value discovery, value is determined by the improvement in managing and applying analysis of data through analytics. Value in value creation is created by the use of IT systems such as Enterprise Resource Planning (ERP), Advanced Planning and Scheduling (APS), Customer Relationship Management (CRM), or decision support systems, enabling better decision support for the business processes. Central to all three perspectives is that the IT systems that manage business processes, i.e. EIS, must be integrated with analytics and relevant data sources to enable better decision support, providing relevant insights and actions for the company's business processes to increase value generation and capture value.

Brinch (2018) identifies three starting points for data initiatives: data first, problem first, and business first. Data-first initiatives start from data to identify insights or actions relevant for the business (Vanauer, Bohle, and Hellingrath 2015). Problem first starts from having a specific business problem identified and exploring the available data to address the business problem (Chen and Zhang 2014). Business-first initiatives rely on having a business objective or vision and then employing data initiatives to meet the objective (Vanauer, Bohle, and Hellingrath 2015).

While the exploration of potential value by employing a data-first approach has tempted many companies, Herden (2019) finds that data initiatives rarely produce value. Instead, the most successful starting point is to start from a relevant business problem and subsequently apply analytics to data to discover and create value. Further, value from analytics initiatives can be categorised as either discoveries, i.e.

provide value in learning, or by providing analytic products that provide value in use (Herden 2019; Larson and Chang 2016; Viaene and Van Den Bunder 2011).

It should be clear that value can be understood differently, and to achieve a competitive advantage, all three value perspectives need to be considered. Value must be discovered from data by the use of analytics created by transforming and integrating the analytics solution with IT systems, triggering actions or insights, and capturing the value by aligning the actions and insights with the company strategy.

As a consequence, for companies to generate value from their company data, they must address business-relevant issues by applying analytics to external data and provide insights and actions which are integrated with business process IT systems, i.e. EIS. However, as the focus of this thesis is on the integration of analytics and EIS, value capture will not be considered. Instead, this thesis addresses value discovery and value creation, as well as the analytic value intersection. Thus, value in this thesis is scoped to manage the generation of value by the use of analytics in EIS by processing the available data into a valuable output.

2.2. Research themes

The domains of analytics, O&SCM, and EIS are all deeply complex and can be researched from many angles and perspectives. Additionally, there are multiple discussions and disagreements on definitions of different phenomena within the fields, such as defining SCM, big data, and analytics (Asmussen and Møller 2020; Ellram and Cooper 2014). The domains can be viewed from many perspectives, such as a mathematical perspective in improving algorithms; a decision-making perspective in how workers can incorporate predictive analytics for improved decision-making; social perspectives, such as researching the interaction between technology and workers; and even trying to define concepts such as 'big data'. The difficulty of positioning the research is exemplified in Asmussen and Møller (2020), where 650 papers within the themes of analytics, EIS and SCM had to be divided into twenty different topics due to the nature of having different research perspectives and themes. As a consequence, it becomes necessary to clearly define not only the research domains, but also the research perspectives and positioning within the research themes.

Therefore, this section presents an overview of the themes of O&SCM, analytics and EIS. The section is concluded by summarising the findings to present the positioning for the thesis within the three research themes.

2.2.1. Operations and Supply Chain Management

O&SCM management deals with planning and control of material and information flows, both internally and externally of the company (Cooper, Lambert, and Pagh 1997). Traditionally, operations are concerned with optimising the internal resources to become more efficient and effective by such activities as material planning, maintenance and analysis of production systems. Supply chain management addresses the external part of the company optimising and coordinating with key players in the supply chain, e.g. suppliers and logistic teams. A typical depiction of an O&SCM flow is a network of materials, information and services processing linked with the characteristics of supply, transformation and demand (Chen and Paulraj 2004). The O&SCM field was originally coined by industrial consultants who advanced the field in 1982 (Oliver and Webber 1982) but was not accepted by academia until 1990, when the first academic paper on supply chain management was published (Ellram and Cooper 1990). Since then, the definition of O&SCM has been greatly discussed, where some argue that the field is still ill-defined and may not even be a discipline in its own (Ellram and Cooper 2014). A main issue in defining O&SCM is that the field is wide ranging, from marketing, CRM, demand management, order fulfilment, manufacturing flow management, supplier relationship management, product development and commercialisation, and return management (Ballou 2007). As a consequence, many definitions of the field have been proposed (see Croom, Romano, and Giannakis 2000; Lummus and Vokurka 2000; Mentzer et al. 2001). The breadth of the field has led to different perspectives of the field, such as a logistics perspective (Ballou 2007; Cooper, Lambert, and Pagh 1997; Mentzer, Stank, and Esper 2008), marketing perspective (Douglas and Cooper 2000; Jüttner, Christopher, and Godsell 2010), operations perspective (Chen and Paulraj 2004; Mentzer, Stank, and Esper 2008; Rudberg and Olhager 2003), and a financial perspective (Lambert and Burduroglu 2000; Martin and Lynette 1999). In an extensive literature review, Ellram and Cooper (2014) extend the perspectives of SCM and present five different perspectives: process, discipline, governance structure, philosophy and function. They further comment that even though there are many perspectives on the definition of SCM:

“. . . there is actually a high level of agreement on the overall concept of the supply chain”.

and

“. . . testing and studying the entire supply chain to apply the concept of supply chain management is very complex. Thus, as academics have moved from attempting to define the SC concept to trying to test SCM theory and applications, the tendency is to test one part or aspect of supply chain management”.

As such, it can be complex to address the issues of the entire supply chain, and academics are urged to present their positioning for research within the supply chain field, such as not claiming to study the entire supply chain in a problem related only to logistics.

It is therefore important for this thesis to be transparent and clear about its positioning within the O&SCM field. The overall objective of the thesis is on the integration of analytics in the O&SCM business process by the use of EIS for improved value discovery, value creation, and the analytics intersection from enterprise data. Consequently, the focus is on the process and thus is the perspective of this thesis on improving the operational business processes as defined by (Ellram and Cooper 2014), which is

"Supply chain as a means for linking structured activities designed to produce an output for a particular customer or market (Davenport 1993); it can also be a means to improve/coordinate processes . . . This also includes specific perspectives, such as information technology as a means to facilitate coordination or integration".

The research in this thesis is mostly focused on improving the internal operations of a company and has little focus on other aspects such as marketing. Further, most of the research in this thesis is on improving the functional level of the supply chain as defined by Mentzer, Stank, and Esper (2008), but most of the findings can likely also be applied to an intra- or inter-firm level. The following section will present and discuss the perspective of the O&SCM business process.

1.2.1.1 O&SCM business processes

While there is a disagreement on what defines O&SCM and how one can view the field, there is a general agreement that business processes are at the core of O&SCM (Burgess, Singh, and Koroglu 2006). Many business process frameworks have been proposed and used by both academics and practitioners, where popular examples are the SCOR model (Stewart 1997), Porter's value chain (Porter and Millar 1985), Materials Planning and Control, (Jacobs et al. 2011), and Sales and Operations Planning (S&OP) (Ling and Goddard 1988). The frameworks are used to manage the processes of a company to reach higher levels of competitiveness, i.e. reaching low cost, high flexibility, quality, delivery (Hayes and Wheelwright 1984; Skinner 1969), innovativeness, time, delivery speed, and delivery reliability (Corbett and Wassenhove 1993; Miller and Roth 1994). However, the use of standardised frameworks is often not enough for reaching higher levels of competitiveness, as the frameworks need to fit specifically to the focal company (Jonsson and Holmström 2016; Sousa and Voss 2008). A key issue is that companies are in different environments and have different supply chain configurations, which means that there is no standard way of addressing the uncertainty of the individual company. Davis (1993) defines three sources for supply chain uncertainty, which are supplier uncertainty (e.g. lateness and inconsistency), manufacturing uncertainty (e.g. machine breakdown and process performance), and demand uncertainty (e.g. irregular orders and forecast errors).

There is no doubt that the O&SCM process framework that has been used for decades has stood the test of time, as it is still in use at companies today and has only seen minor adjustments over the years. Thus, the standard process frameworks do work; however, they need to account for the increasing uncertainty that companies are facing. To address uncertainty, companies need to make better decisions by pre-emptively predicting the future and taking appropriate action. Due to the rapid development in technology over the last decades, companies have been able to process larger volumes of enterprise data by advanced analytical methods in a data-driven decision manner. Examples are predicting supplier delivery times (supplier uncertainty), predicting machine breakdown (manufacturing uncertainty), and predicting sales orders (demand uncertainty). Although many analytical methods have been developed in academia to improve data-driven decision-making, especially in operations research (OR), there is a lack of application of data-driven decision-making in the industry (Jonsson and Holmström 2016). A key issue is that EIS is costly to customise in both time and funds. This is an issue, as the demands for companies to adjust to changing market conditions and increase in competitor's efficiency means that companies must continuously adjust how they make decisions, and consequently, must change their IT systems. For example, in EIS, it is difficult to incorporate new data sources and process high volumes of data with machine learning models without high costs (Asmussen and Møller 2020; Jonsson and Ivert 2015).

2.2.2. Analytics

The field of analytics suffers from the same problem as O&SCM of being ill-defined and, consequently, researchers should clarify how analytics is understood and used in their research. Clarifications on how analytics is understood in this thesis are extensively explained in Asmussen and Møller (2020) and Asmussen, Jørgensen, and Møller (2020). However, this section will present a summary of the two articles in terms of defining and scoping analytics.

Analytics includes many terms within the supply chain field: Business Intelligence (BI), Business Analytics (BA), Supply Chain Analytics (SCA), Supply Chain Data Science, Data Science, Analytics, Big Data Analytics (BDA), and operations research (OR) (Akyuz and Rehan 2009; Asmussen, Jørgensen, and Møller 2020; Chae et al. 2014; Chen, Preston, and Swink 2015; Hazen et al. 2014; Herden 2017; Oztekin et al. 2016; Souza 2014; Waller and Fawcett 2013; Xing et al. 2013).

When analytics is used in this thesis, unless specified, the term includes all distinctions. The thesis uses the definition of analytics by Davenport and Harris (2007), which is:

"The extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions. The analytics may be input for human decisions or may drive fully automated decisions".

The analytics process is seen as a group of approaches, procedures and tools and includes everything from gathering, processing, manipulating and modelling to visualising data (Asmussen, Jørgensen, and Møller 2020; Trkman et al. 2010). The purpose of analytics is to solve a business problem, where the problem is understood as a business question (Bose 2009; Larson and Chang 2016) or a business objective (Asmussen, Jørgensen, and Møller 2020; Seddon, Calvert, and Yang 2010; Viaene and Van Den Bunder 2011). Analytics is rooted in IT systems, which can be used by a broad group of decision-makers and can be partially or fully automated (Asmussen, Jørgensen, and Møller 2020; Herden 2019; Liberatore and Luo 2010). Further, analytic and ordinary IT integration projects are seen as notably different (Asmussen, Jørgensen, and Møller 2020; Marchand and Peppard 2013; Viaene and Van Den Bunder 2011).

2.2.2.1 *The analytics paradigm*

There is a paradigm shift within analytics in O&SCM, where the historical use of analytics methods, e.g. OR, predominantly looks for causation, where analytics is now often used to discover correlations based on large, feature-rich data (Breiman 2001; Delen and Zolbanin 2018). In essence, the paradigm shift is moving away from requiring analytics to aim for causation and is instead relying on correlation. The research director of Google, Peter Norvig (2009), comments:

"If the model is going to be wrong anyway, why not see if you can get the computer to quickly learn a model from the data, rather than have a human laboriously derive a model from a lot of thought . . . In complex, messy domains, particularly game-theoretic domains involving unpredictable agents such as human beings, there are no general theories that can be expressed in simple equations like F = m a or E = m c^2 . . . Having more data, and more ways to process it, means that we can develop different kinds of theories and models. But that does not mean we throw out the scientific method. It is not "The End of Theory." It is an important change (or addition) in the methodology and set of tools that are used by science, and perhaps a change in our stereotype of scientific discovery."

This paradigm shift is mainly driven by the introduction of BDA, where bigger datasets and more processing power are available to analyse both structured and unstructured data (Asmussen, Jørgensen, and Møller 2020; Barbosa et al. 2017; Gandomi and Haider 2015; Kache and Seuring 2017; Nguyen et al. 2017). While there is a new paradigm in the use of analytics, it does not mean it replaces the old paradigm. The toolbox for the supply chain data scientist has simply gotten bigger, which historically mostly consisted of OR methods, but now also includes other advanced analytical methods such as machine learning.

1.1.1.1 Creating and capturing value from analytics

The aim of constructing and implementing analytic solutions is to become more competitive by generating value for the company. Value is generated by transforming data into insights and actions, which facilitates improved execution and planning processes. However, possessing analytical capabilities and analysing data only brings value once a user or system acts upon the information or insights (Asmussen, Jørgensen, and Møller 2020; Gandomi and Haider 2015; Herden 2019; Holsapple, Lee-Post, and Pakath 2014; Kiron et al. 2011; Lavalle et al. 2011; Seddon, Calvert, and Yang 2010). It is therefore of high importance to include the users, and not just the analytics experts, in designing, constructing and implementing an analytics solution, as no value is created if an analysis is not followed by action (Davenport and Harris 2017).

As a consequence, the consumability of insights becomes important, where the following factors are found to hurt the consumability (Herden 2019).

- Data issues (integration, quality, management, protectionism and infrastructure)
- Lack of fit to process
- Unintuitive solutions
- Low availability
- Data not presented in the right format, e.g. alerts, visualisation
- Failure to reduce the effort of making a decision
- Failure to make a solution useable without too much analytical effort

As a result, many companies are finding it difficult to get value out of analytics projects (Davenport and Harris 2017), an issue which can become bigger as the cost of extracting insights and actions from data is becoming more costly as data volumes continue to rise (Bose 2009; Kache and Seuring 2017; Marchand and Peppard 2013; Nguyen et al. 2017). Extracting value from an analytics solution requires that the solution can address a business problem relevant for the specific company based on specific processes, people and tasks (Ghasemaghaei, Hassanein, and Turel 2017). Consequently, an analytics project should start from a business problem, instead of starting from data, as it is more likely to develop relevant and useable solutions and is better at motivating sponsors (Herden 2019). Consequently, an analytic solution should solve an issue within the business context and, as a result, copying competitors' analytic solutions provides no value (Herden 2019; Lai, Sun, and Ren 2018).

2.2.3. Enterprise Information Systems

The history of EIS is long and has moved from being a simple bookkeeping stand-alone system to integrating networks and databases, supporting business processes, information flow, and reporting and data analysis in a company (Romero and Vernadat 2016). The evolution of EIS offerings has evolved from supporting Materials Requirement Planning (MRP) to Manufacturing Resource Planning (MRP/II), ERP/I, and last to ERP/II which supports the 'extended enterprise' and enables the inter-organisational collaboration embracing supply, design and engineering business functions" (Møller 2005; Romero and Vernadat 2016). Now, future editions of EIS aim to create a borderless enterprise, supporting collaboration across internal and external borders (Hurbean and Doina 2014).

EIS is defined as "*software systems for business management, encompassing modules supporting organisational functional areas such as planning, manufacturing, sales, marketing, distribution, accounting, financial, human resources management, project management, inventory management, service and maintenance, transportation and e-business*" (Rashid, Hossain, and Patrick 2002).

There are many modules of EIS which each address different business issues: ERP, Manufacturing Execution Systems (MES), CRM, APS and BI. ERP systems can be viewed as the central EIS, which integrates modules such as logistics, procurement, sales, marketing, human resources, finance, e-commerce (electronic catalogue on-line purchasing, status-check facilities), and e-procurement (automating online ordering, order status, ship notice, payment and invoicing) (Møller 2005; Romero and Vernadat 2016). MES, on the other hand, is used to manage the production of goods, enabling the detailed execution and control of the production, down to a production unit in real time (Asmussen, Jørgensen, and Møller 2020). The MES system is viewed as a competitive enabler, as it can record enormous amounts of data which can be processed by advanced analytical methods (Asmussen and Møller 2020). CRM handles customer relations, such as sales activities and service tickets, manages campaigns, and processes customer data to generate valuable information. The current trend is to also make use of social media (Kim and Lee 2009; Quinton 2013).

An APS system is defined as any computer program that uses advanced mathematical algorithms or logic to perform optimisation and/or simulation on finite capacity scheduling, sourcing, capacity planning, resource planning, forecasting, demand planning and others (Ivert 2012). APS is typically used when simple planning methods cannot adequately address complex trade-offs (Ivert and Jonsson 2011). BI solutions have historically been using data warehouses to process data analytically by Online Analytical Processing (OLAP) through Extract, Transform and Load (ETL), in contrast to the transactional focus from other EIS modules mainly using Online Transaction Processing (OLTP) (Kleppmann 2017). BI solutions have mostly been used to create reports and statistical data analysis by descriptive and diagnostic analytical methods (Asmussen and Møller 2020; Romero and Vernadat 2016).

Unsurprisingly, different companies have different system landscapes consisting of different EIS modules and different configurations and customisations of the modules. While the EISs can be stand-alone, they are often integrated, either tightly or loosely, with both internal and external IT systems.

Romero and Vernadat (2016), in a state-of-the-art paper, identified current and future trends within EIS. They find that most enterprises either have or are moving towards a service-oriented architecture (SOA), which is a collection of services that are loosely integrated. Companies can, as a result, have hundreds of information systems, depending on the size of the company. They argue that the future of EIS will become ‘borderless’, introducing new technologies such as mobile, social media, and IoT, which can be supported by Workflow Management Systems such as BPM. EIS will move from monolithic stand-alone applications to distributed cloud service-oriented solutions that can dynamically create and maintain ‘just enough’ integration of information, control and material flows (Romero and Vernadat 2016). They predict that the advent of cloud computing will have a big impact on EIS by increased use of Anything-as-a-Service (Xaas), for example, and will include the capabilities to utilise and integrate the latest technological developments. Further, the rise of big data is set to have a big impact, as many heterogeneous data can be analysed in real time to provide faster and better information for systems and users.

As the environment for companies is predicted to change at an unprecedented rate, EISs must also follow and support new business models, legal regulations, and market situations (Ernst and Schneider 2010). As a consequence of the fast-changing environment, EIS must be able to address new processes, implement enhancements, and fine-tune the current IT system, as changes cannot be seen as an exception but a normality (Arora and Nirpase 2008). Further, while the integration of EISs becomes mandatory, the need to make faster integration becomes a prerequisite for competitiveness. Consequently, this means that integration will have to move from design-time integration to run-time integration. Accordingly, future EISs are predicted to become more loosely coupled, less rigid, and less pre-defined solutions that can support business agility and rapid enterprise solutions (Romero and

Vernadat 2016). Therefore, it is to be expected that analytics solutions, which can support the business workflow, are loosely coupled and need to be able to quickly integrate into the companies' EIS.

2.3. Relevancy and purpose of the thesis

Having presented the research areas of the thesis, this section will discuss and argue the relevancy and purpose of the thesis.

Although companies become more competitive by the successful use of enterprise data, it is still unknown specifically *how* that is done. Jonsson and Holmström (2016) argue that the mechanisms, i.e. processes, behaviours and responses triggered by interventions, within SCA literature are not well understood, and as a result, the outcome of an intervention is unknown. Consequently, companies are having difficulties in obtaining a competitive advantage from integrating analytics with EIS (Barbosa et al. 2017).

Companies must introduce predictive and prescriptive analytics into their operations and supply chains to become more competitive, which requires the use of advanced software applications. However, standardised EIS platforms, as well as dedicated planning software (i.e. predictive and prescriptive analytics packages) are still not widely implemented in practice (Jonsson and Ivert 2015). However, the software packages are available for companies, where data science platforms and languages, such as R, Python and Julia, are offered as free open-source solutions. Further, analytical methods for O&SCM have been developed over many decades by OR researchers and are seen as key to generating impactful actions and insights (De Ugarte, Artiba, and Pellerin 2009; Holsapple and Sena 2001), which methods need to be integrated with the EIS of the companies.

Additionally, the research within the three research themes is seen as 'applied research domains', and consequently, it is essential to not only extend the knowledge base, but also to ensure the practicality and relevancy of the research for companies. This is not to state that developing theory is not relevant; instead, the purpose of generating theory should be to generate practical theory. In their critique of the development of non-practical supply chain planning theory, Jonsson and Holmström (2016) find that most concepts and models within supply chain planning have been available in textbooks and known by consultants for many decades, and point to the lack of studies for the adoption of these models and concepts in practice. Research must therefore be actionable for practitioners, where it should be possible to pre-emptively provide evidence of intended outcomes and account for the specific context within which the research is conducted. Much of the recent research within the area of SCA has mostly focused on singular aspects of big data and technological improvements (Arunachalam, Kumar, and Kawalek 2017; Brinch 2018; Brinch et al. 2018; Fosso, Akter, and Paper 2015; Kache and Seuring 2017; Nguyen et al. 2017; Zhong et al. 2017). As a result, there is a lack of research on the adaptation and integration of analytics in O&SCM.

Consequently, this presents a research opportunity for researching how to successfully integrate the use of analytics in the O&SCM domain supported by EIS. Therefore, the purpose of this thesis is to identify the *how* and *what* drives a successful integration of analytics with EIS in an O&SCM setting for improved value discovery, value creation, and the analytic value intersection. The intended outcomes of the research of the thesis are an identification of mechanisms for integrating analytics with EIS and a framework that operationalised the integration to close the gap from promise to practice. Thus, the research must identify the general issues and challenges of integrating analytics with O&SCM and EIS, and propose solutions for how to overcome these challenges. The research follows a design science methodology, where the combination of academic knowledge with practical applications in a real-world setting will enable the research to create prescriptive knowledge that is relevant for both academics and practitioners. In summary, this PhD thesis is an attempt to create research interest and solutions for closing the gap between practice and the promise of integrating analytics and EIS.

2.4. Presenting the research framework

The research framework is depicted in *Figure 4*.

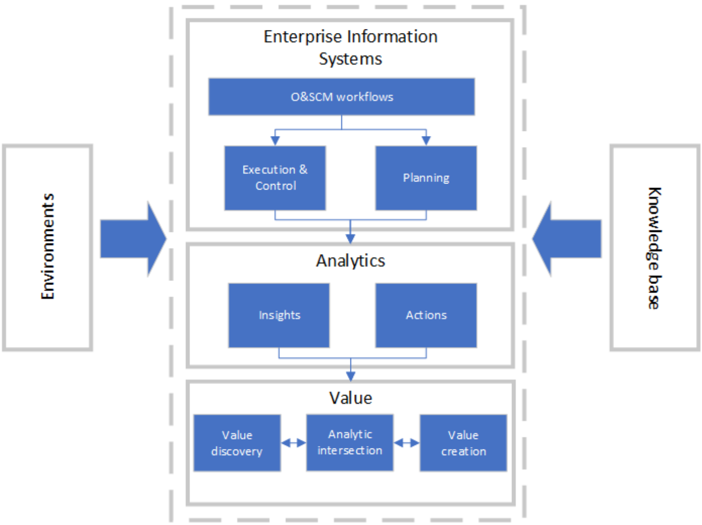

Figure 4. Research Framework.

The framework depicts the relation between the value definitions of value discovery, value creation, and the analytic intersection, which is generated when better insights and actions have been provided. Better insights and actions are provided by the use of analytics for execution, control and planning processes in the O&SCM business processes, which are managed by EIS.

The thesis aims to understand the mechanisms of increasing the value output by the use of analytical methods to create better insights or action for the O&SCM business workflow. These mechanisms will be researched from two perspectives, inspired by design science. First, mechanisms are identified by researching and reviewing the academic knowledge base to construct a theoretical foundation. Second, mechanisms will be identified and prescriptively created by constructing analytical artifacts in an O&SCM environment. The environment in this thesis is at Arla Foods.

As mentioned in section 2.2, it is paramount to be clear on the research positioning within the three research themes, as they are all somewhat ill-defined. The research theme of O&SCM can be viewed as a process, a function, a governing structure, a discipline, and as a philosophy (Ellram and Cooper 2014). Further, analysing O&SCM can be done from an external perspective (researching downstream or upstream perspectives), an internal perspective (focal-firm perspective), or a full supply chain perspective covering all mentioned aspects (Douglas and Cooper 2000). This thesis will apply a process perspective, mainly focusing on the internal focal-firm perspective. Consequently, the use of analytics is also seen as a process, and not as a method in itself. Thus, the identification of mechanisms related to analytics will be based on a process view and not on improving current tools or methods. The incorporation of EIS and the integration and management of business processes and analytics entails that the research will be viewed from an IT perspective.

Further, the use of EIS is central to the successful management of O&SCM processes and the integration of new insights and actions. Thus, the focus of this thesis is on the integration of IT, analytics and O&SCM business processes and focuses on the operational and practical issues of integration to make the research relevant for both practitioners and academics.

The research in this thesis is positioned in the intersection between the three research themes of O&SCM, analytics and EIS and applies a perspective that can be described as an “IT enterprise business process integration” perspective. The perspective is to be understood as integrating analytical processes and artifacts with O&SCM business processes through an IT EIS integration to increase value from value discovery, value creation, and the analytic intersection.

The expected contribution is to provide both practitioners and academics with an understanding of the mechanisms that generate value, where most of the current research focus has been on defining value, researching the management of IT implementation and assimilations, or on technical aspects such as implementing or using BDA.

2.5. Research objective

The research in this thesis builds on the themes O&SCM, analytics and EIS and specifically addresses the integration of analytics into O&SCM business processes with EIS. As previously stated, the motivation for this thesis was to pursue theoretical and practical relevant research, which can aid companies in creating value from their enterprise data by the use of analytics integrated with the O&SCM business workflow. Therefore, the research objectives of the thesis are:

Objective 1: *To identify the value mechanisms at the intersection of value discovery and value creation by integrating analytics with EIS.*

Objective 2: *To create an approach based on the value mechanisms in the intersection of value discovery and value creation by integrating analytics with EIS.*

The purpose of the first research objective is to set a baseline on which analytic integration projects with EIS can be based. The intention is that by better understanding the mechanisms of integrating analytics with EIS, it will make it easier to generate expected outcomes, which hopefully will result in more successful analytical projects. The mechanisms will be researched as part of a design cycle where the academic knowledge base is explored by constructing and deploying analytical artifacts in a naturalistic environment. Additionally, the identified mechanisms will be used as a foundation for constructing a value framework.

The purpose of the second research objective is to operationalise the integration of analytics with EIS, as to present instantiations which present for both academics and practitioners how the mechanisms and value framework can be utilised in the form of an approach. Additionally, the second research objective is used to evaluate the findings of research objective one in a real-world setting. The approach is constructed based on the perspective of “IT enterprise business process integration” and will be using currently available methods and technologies.

Chapter 3. Research design

This chapter clarifies the research position and research design used in this thesis. The first part describes the research philosophy, which is followed by a discussion on different research forms, where the research form design and evaluation research is selected. Following is a description and discussion on the use of design and evaluation research, where the themes of balancing practical and academic relevance and ensuring rigor are discussed. The final section describes the research design and methodology of the thesis, which is concluded by stating the evaluation metrics for the research objectives.

3.1. Research philosophy

Research philosophies are based on ontologies and epistemologies, where ontologies inform a scholar on the nature of the approach to the phenomenon examined, and epistemologies refer to the methods used to understand a phenomenon (Van de Ven 2007). Further, two positions exist within Western philosophies, i.e. the positivistic and relativistic positions (Van de Ven 2007). The positivistic position is to view the world as external or independent to the research of the researchers as ontological objective. Consequently, a positivistic researcher believes that reality can be studied without affecting it as an epistemological objective. A positivistic researcher creates new knowledge and theories by observing reality through objective observations. On the other hand, a researcher with a relativistic view considers reality as constructed by people and society using an ontological subjective view. Thus, the relativism researcher takes on an epistemological subjective position, where reality is created by the interaction between individuals. As such, the reality and the research of researchers impact each other. The knowledge generated by the relativism researcher is determined by the concepts introduced to reality.

The application of integrating analytics with EIS is at its core, an integration of business processes with information systems that is fitted to an organisational structure and infrastructure. This configuration exists even if the author, other researchers, or practitioners are aware of them or not. It could therefore be argued that the research should take on an objective ontological position. However, the integration between business processes, analytics, the organisation structure and infrastructure are constructed and determined by the workers and managers of an organisation. The configuration is created by the workers and managers applying models and concepts which are based on their subjective view of reality. As such, the studied environment in this thesis (Arla Foods) is affected by the workers and managers at that company, where the research of this thesis is further affected by the author's understanding of the company's reality and applied concepts and knowledge. Thus, the reality for the author is determined by his knowledge and understanding of concepts, but reality exists independently from the author's understanding. Consequently, the knowledge of reality for the author is considered incomplete.

The role of theory is to explain or predict reality, but they are never perfect and can at all times be replaced by better explanations of reality. Contributions in the applied research fields of analytics, EIS and O&SCM usually aim to solve a problem by proposing new methods or models. New contributions therefore need to be evaluated against a real-world environment to lead to significant knowledge growth. However, companies have unique configurations of IT systems and business processes, which severely hinders the ability to generalise experimental outcomes. Thus, while not complete, the understanding of reality improves for every application of research. The approach for this research is therefore to re-evaluate previous understanding of reality, with new research contributions. Additionally, the research in this thesis is based on the understanding that science is a process of error correction (Van de Ven 2007).

Consequently, the view of this thesis is critical realism, which seeks to solve problems by understanding mechanisms (Coughlan et al. 2016). Critical realism is based on different layers of reality, which can be revealed through the systematic application of science (Chira 2002). The layers consist of the empirical, the actual, and the real layer (Bhaskar 1978). The empirical layer is made of events and experiences made by observations, the actual layer consists of all events whether they have been observed or not, and the real layer consists of the processes and mechanism that generate events (Coughlan et al. 2016). The critical realism is aligned with design science practices, where the goal is to solve problems or make improvements by understanding the events and mechanisms, whether they have been observed or not (Coughlan et al. 2016). Consequently, the use of critical realism enables research to be relevant for both academics and practitioners in solving real-life problems, but at the same time supports a conceptual theory building cycle (Coughlan et al. 2016).

3.2. Research forms

There are many ways of conducting research, and it can be difficult to navigate and identify the best research form. To aid in navigating different research approaches, the framework from Van de Ven (2007) has been selected. The reason for selecting this framework is that it aims at creating a relationship between theory and practice, by creating practically relevant outcomes, and at the same time advancing scientific knowledge. The framework is related to organisation and management studies, which is a major part of a successful integration of analytics with EIS. The approach of the framework, called engaged scholarship, encourages collaboration between researchers and practitioners, which will consider both practical problems and gaps in the knowledge base. Last, the philosophical position of the engaged scholarship is also critical realism, which creates a philosophical fit with the research philosophy of this thesis.

The engaged scholarship proposes four research forms, which are depicted in *Figure 5*. The research forms depend on the purpose of the research and the perspective of the research. First, the research purpose is defined by specifying if the purpose of the research is to examine basic questions of description, explanation and prediction or on applied questions of design, evaluation or action intervention (Van de Ven 2007). Next, the research perspective is clarified by viewing the research as an external observer or internal participant (Van de Ven 2007).

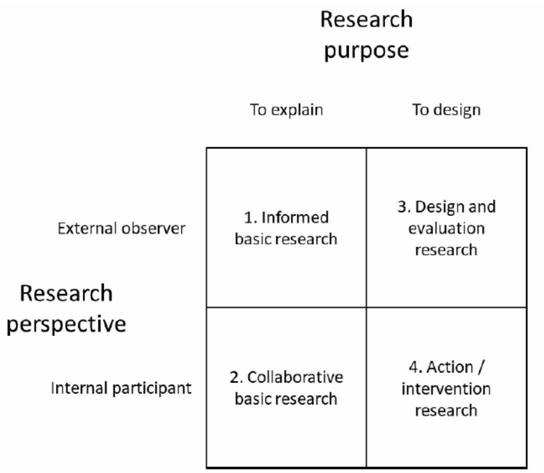

Figure 5. Research forms of engaged scholarship (Van de Ven 2007).

The four research forms are described as:

1. *Informed basic research* – describes, explains, or predicts a social phenomenon (Van de Ven 2007). The researcher is detached from the investigation as an external observer but can seek advice and feedback from key stakeholders and informants during the research activities.
2. *Collaborative basic research* – produces basic knowledge about a complex problem or phenomenon in a collaboration between teams of internal participants and external observers (Van de Ven 2007).
3. *Design and evaluation research* – examines normative questions that deal with the design and evaluation of policies, programmes or models for solving practical problems (Van de Ven 2007). The research seeks to provide alternative solutions to applied practical problems. The evaluation

of solutions is usually done by external observers to obtain evidence-based knowledge that is impartial and legitimate.

4. *Action/intervention research* – uses a clinical approach to diagnose and treat a problem of a specific client (Van de Ven 2007). Research is created by a learning process where the researcher engages and intervenes with a specific client. Systematic methods of data collection, feedback, reflection and action are used and make use of knowledge whether it is basic or design science knowledge (Van de Ven 2007).

The purpose of this thesis is to investigate *how* companies can become more competitive by generating value in value discovery, value creation, and the analytic intersection of integrating analytics with EIS. To understand the *how*, the research must investigate the connection between the empirical, actual and real layers of reality. It has been observed in the empirical layer that some companies become more competitive through the use of analytics. However, this does not occur in all cases, which entails that all events in the actual layer are not understood. Consequently, the real layer must be investigated to understand the mechanisms and processes of generating value by integrating analytics with EIS.

The research objectives of this thesis are to understand the mechanisms for integrating analytics with EIS and to construct an approach, not for just one company, but most companies. The selected research form must provide generalisable answers to the research objectives. Further, to create an understanding of the mechanisms of a successful integration of analytics with EIS, new knowledge and solutions need to be constructed and evaluated. The explanatory research forms of informed basic research and collaborative basic research do not properly address these concerns. On the other hand, both design and evaluation research and action/intervention research do, but the latter does not generalise the findings, as the purpose of the research form is to address a specific problem for a specific company. Thus, the selected research form of this thesis is the design and evaluation research form. However, this should not be understood as to only be using that research form for all the research, but it will be used as the main method guiding the research of the thesis. For example, to identify mechanisms of integrating analytics and EIS, a solution or artifact can be constructed and deployed in a specific context at a specific company to generate insights into mechanisms.

The research of the thesis follows the engaged scholarship diamond model, which is a process model consisting of four process steps depicted in *Figure 6*.

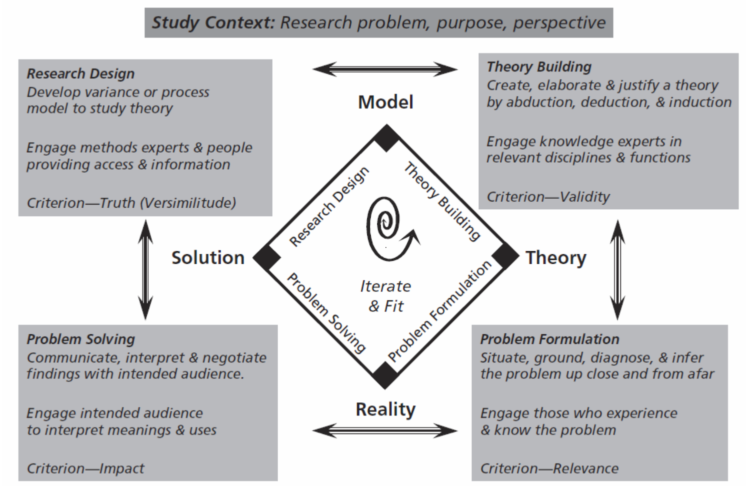

Figure 6. Engaged scholarship diamond model (Van de Ven 2007).

The model proposes that research is iterative and can start from any of the four process steps. Some researchers might start from a theory and then search for the problem in practice, and others might use their methodological tools to develop theory (Van de Ven 2007). The research of this thesis has started from a problem formulation state, where it has been found that the mechanisms for the creation of value by the use of analytics in O&SCM companies are unknown. This has also been the motivation for doing the PhD study. The problem formulation has been addressed by an iterative problem solving and theory building process. The research has simultaneously been conducted by exploring the challenges in the real world, i.e. at Arla Foods, and by reviewing and exploring the academic knowledge base. Once satisfactory results had been achieved, a research design for the thesis was constructed. The details of the research design are described in section 3.3 and 3.4.

The research of this thesis has been conducted at Arla Foods as a part of the MADE programme, where the author is an employee of Aalborg University. This warrants that the research has to address the interests of all three stakeholders. The research should therefore be practically relevant for the focal company (Arla Foods) and the other members of the MADE programme and industry in general and deliver new relevant academic output for Aalborg University. A consequence of this is that while the design and evaluation research form will guide the overall method for the thesis, several other methods, such as action design research and a structured literature review, have been applied. Thus, the foundation of the research in this thesis has been conducted in the environment of Arla Foods and by reviewing and comparing that to the academic knowledge base.

3.3. Design and evaluation research

The research form design and evaluation research has been found most suitable for this thesis, but it has not been explained in detail why and how the design and evaluation research form is intended to be used in this thesis, which is the intention of this section.

To summarise, the outcome of the thesis has three main stakeholders: Arla Foods, MADE and Aalborg University. Both Arla Foods and MADE expect that the research outcome will be practical in the sense that the outcome of the research must solve practical problems that they are facing. An explicit expectation from Arla Foods has been that artifacts will be constructed on the company's enterprise data to address a company problem. Though there have been no expectations of directly implementing the artifacts into the company's business processes, they value the prescribed knowledge generated by constructing the artifacts. On the other hand, Aalborg University expects that the research outcome will have the rigor of a PhD level, no matter the research form selected, and have an adequate number of journal papers published or submitted.

Consequently, the research needs to provide IT artifacts that satisfy the expectations of Arla Foods, MADE and Aalborg University. However, the framework by Van de Ven (2007) provides little guidance in how to create IT artifacts. The research mode mainly addresses design and evaluation from a social science perspective that deals with the design and evaluation of policies, programmes and models. Consequently, this thesis is built on DSR, where the combination of constructing artifacts and making use of the academic knowledge base will lead research on providing outcomes relevant for all stakeholders. The remainder of this section will describe DSR and how relevance and rigor can be evaluated.

3.3.1. Design science research

Design as an activity has its roots in engineering and the science of the artificial (Simon 1996). Design science seeks to create and evaluate artifacts that solve organisational business problems (Hevner, March, and Park 2004). Further, the design process is both seen as a process and a product, respectively describing the world as acted upon and sensed (Hevner, March, and Park 2004). DSR needs to contribute to the archival knowledge base of foundation and methodologies by addressing important unsolved problems in innovative ways (Hevner, March, and Park 2004). Thus, the research contribution of design science needs to either provide innovative artifacts or new constructs, models, methods, instantiations or methodologies (Hevner, March, and Park 2004).

The design science guidelines of Hevner, March, and Park (2004) and Peffers et al. (2007) are followed in this thesis. The overall research of the thesis is guided by the use of Hevner, March, and Park's (2004) framework, where a design process is initiated based on the needs of the business with applicable knowledge from the knowledge base. The design process uses information from a practical environment, such as people, organisational processes and technology, as well as theories, frameworks and methodologies from the knowledge base. The design process consists of construction and evaluation processes. The outcome of the construction process is either a product or process artifact. The artifact is then evaluated in terms of addressing the problem at hand. The design process is iterative and ends once the evaluation of the artifact is satisfactory. The framework by Hevner, March, and Park (2004) does not specify how to conduct the research using their framework, and subsequently, the process model from Peffers et al. (2007) has been applied, which is depicted in *Figure 7*.

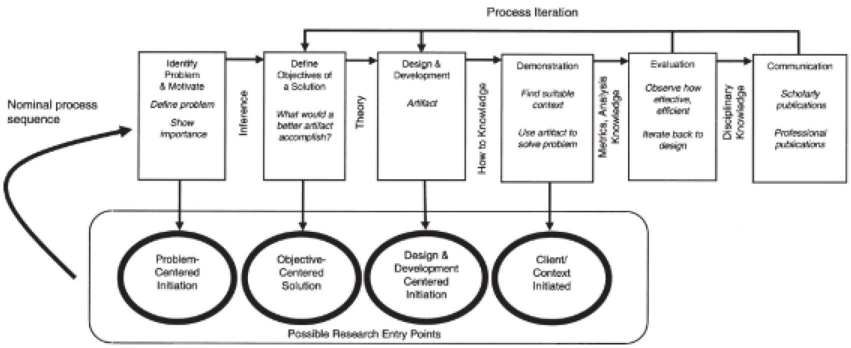

Figure 7. DSR process model (Peffers et al. 2007).

The research of this thesis has begun by defining the problem, which to summarise was a lack of understanding of the mechanisms to generate value by the use of analytics in the O&SCM domain. The objective of the research was to identify the mechanisms by designing an artifact, where the outcome would be relevant not only for Arla Foods, but for the industry in general. Thus, the objective of the thesis is to create a conceptual design in the form of a process artifact, as a product artifact would likely be difficult to generalise. The process artifact is based on the knowledge gathered from the knowledge base and from constructing, deploying and evaluating several IT product artifacts in the Arla Foods environment. Consequently, the artifact has been used to solve the problem in a real environment. Finally, the process artifact is evaluated by the use of the evaluation parameters presented in sections 3.3.2 and 3.3.3. Last, the outcomes of the research have been communicated to an academic audience in the form of journal papers and by this PhD thesis. The practical outcomes of the research have been communicated to Arla Foods in the form of presentations, meetings, hackathons, as well as sharing the journal papers. Additionally, the research has been communicated to the other members of MADE as part of presentations within the MADE programme.

It can be difficult to describe and evaluate the iterative process of constructing a process artifact and thus the evaluation of the final process artifact becomes essential regarding the problem formulation and problem objective. The next two sections describe how practical and academic relevance and rigor are addressed in this thesis. Part of the two sections are the parameters for evaluation presented and described related to both practical and academic relevance and rigor. The evaluation of the research in this thesis is presented and discussed in the research methodology section 3.4.

3.3.2. Balancing academic and practical relevance

A main purpose of this thesis is to bridge the gap between promise and practice, but it can be somewhat unclear as to what this means. The challenge for bridging the gap is to find the right balance between practical relevant research and academic relevant research. This section will first clarify which practical relevant contributions this thesis proposes, and it ends with a clarification of the relevance of the academic research output.

3.3.2.1 Practical relevance

As a rule of thumb, for research to be practically relevant, it must have the potential to improve the decision-making of managers (Toffel 2016). However, improving decision-making for managers can be done in many ways – Nicolai and Seidl (2010) developed a framework grouping eight forms of practical relevance, depicted in *Figure 8*.

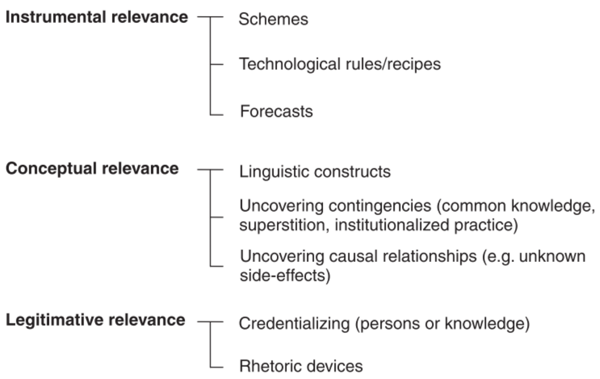

Figure 8. Forms of practical relevance in the management science literature (Nicolai and Seidl 2010).

The eight forms of practical relevancy are grouped into three types of practical relevance: instrumental, conceptual and legitimate. Instrumental relevance refers to research that includes schemes that provide systematics for ordering decision situations, often presented as flow charts or matrixes (Nicolai and Seidl 2010). It can also provide technological rules and recipes that guide practitioners to choose between different courses of action, for example, "if you want to achieve X you need to do Y". Last, instrumental relevance can be used to forecast future developments, e.g. in markets, technology, or share prices. Van Aken (2004) supplements this view and states the importance of instrumental research for practical relevancy. However, he notes that it can be difficult to argue the general applicability, as instrumental research is often developed for a specific domain.

Conceptual relevant research can take three forms, namely linguistic constructs, uncovering contingencies, and uncovering causal relationships. Linguistic constructs aid practitioners by proposing new ways of thinking and communicating about the world and decision situations, often in the form of new concepts or metaphors (Astley and Zammuto 1992; Nicolai and Seidl 2010). Uncovering contingencies provides new perspectives for how decision situations are perceived in the form of new or alternative routes of actions. The uncovering of causal relationships provides practitioners with an understanding of causal relationships and side effects of past research. However, as Bartunek (2007) notes, the identification of casual relationships does not help a practitioner understand what to do in response to them. As such, the research presents a better understanding of a decision situation, but contrary to the contingency form, it does not tell practitioners how to respond to decision situations.

Legitimative relevance refers to either the credentialising or rhetoric devices research form. The research forms refer to the use of jargon from the academic and practical vocabulary, or by referring to theoretical models or research findings to justify the course of action (Nicolai and Seidl 2010).

Nicolai and Seidl (2010) reviewed 450 academic papers for their practical contributions. They find that management scholars are too focused on instrumental relevance and argue that researchers need to do more conceptually relevant research. Thus, researchers are urged to not only aid in choosing the right course of action in a given situation, but also to enhance a practitioner’s understanding of a situation. Consequently, the research of this thesis contributes instrumental and conceptually relevant research. The research of this thesis presents both frameworks and an approach (instrumental relevant research), which helps a practitioner specify what to do in a given situation and presents additional mechanisms and CSF (conceptual research), which aid the practitioners in understanding their situation. Further, the researcher both interacted as a practitioner at the company, gaining hands-on experience, and changed role from actor to observer, as recommended by Toffel (2016), to bridge the gap between practical and academic research. Additionally, the author co-authored a paper with a practitioner to ensure a nuanced view of the research.

3.3.2.2 Academic relevance

Creating academic relevant research means for the realist that theories represent reality, and the two are getting closer over time (Boer et al. 2015). A theoretical research contribution depends on either being consensus-shifting or consensus-creating (Boer et al. 2015); that is, either change the accepted academic position to a new position or create consensus where no consensus previously existed. Hevner et al. (2004) define academic relevance of DSR as “‘heretofore unsolved and important business problems’, where business problems and opportunities often relate to increasing revenue or decreasing cost through the design of effective business processes” (Hevner et al. 2004). Another perspective is provided by Baskerville, Pries-Heje, and Venable (2011), who argue that research is relevant if the outcome of a DSR cycle is properly disseminated and relevant to business needs, now and potentially in the future. The definition by Hevner is seen as unsatisfactory, as it can be difficult to measure economic impact for the research conducted in this thesis. Consequently, the relevance should be measured by an improvement in business processes. However, the contribution of research should not just solve a relevant problem for one company but be used to either create a new position or create consensus, as defined by Boer et al. (2015).

The research for this thesis addressed the academic relevancy by addressing research gaps found via a systematic literature review and combining the findings with the research output of an Action Design Science (ADS) approach conducted in a real environment. Academic relevancy is therefore provided by identifying academic gaps, which is addressed by the identification of a business problem in a real environment. The research outcome creates consensus in a somewhat scattered research domain.

In summary, to find the balance between practical and academically relevant research for this thesis, research must be either consensus-shifting or consensus-creating concerning the academic relevancy; relevant to address a business need now and in the future; and preferably conceptual, instrumental or legitimative practically relevant, in that order. The relevancy of the research in this thesis will be evaluated based on the criteria mentioned in this section, as seen in section 3.4.2.

3.3.3. Research rigor

Hevner et al. (2004) defines research rigor in the context of DSR as ". . . the application of rigorous methods in both the construction and evaluation of the design artifact". They further state that "rigor must be assessed with respect to the applicability and generalizability of the artifact", where the artifact should be constructed in an appropriate environment (Hevner, March, Park, Ram, et al. 2004). In this thesis, the focus on generalizability is essential in that no two application environments are alike. Thus, the generalisable aspect of the thesis is not the artifact itself but the prescriptive process knowledge acquired during the construction and deployment of artifacts. Consequently, knowledge in this thesis has been obtained by the construction and deployment of a sequence of artifacts.

Further, to aid in classifying research contributions, Gregor and Hevner (2013) present a framework for classifying research contributions on three different levels, which is depicted in *Table 1*.

Table 1. Design Science Research Contribution Types.

	Contribution Types	**Example Artifacts**
More abstract, complete, and mature knowledge	Level 3. Well-developed design theory about embedded phenomena	Design theories (mid-range and grand theories)
↕ ↕ ↕ ↕	Level 2. Nascent design theory—knowledge as operational principles/architecture	Constructs, methods, models, design principles, technological rules.
More specific, limited, and less mature knowledge	Level 1. Situated implementation of artifact	Instantiations (software products or implemented processes)

Source: Gregor and Hevner (2013).

The first contribution level is instantiations of a product or process. The second contribution level is general contributions in that it generates knowledge as operational principles, where the third and last level presents mid-range and grand-theories. DSR can produce research at all levels. While the ultimate goal for most researchers is to create mid- and grand theory, the starting point is based on the problem and solution maturity (Gregor and Hevner 2013). Extrapolating on the problem and solution maturity, Gregor and Hevner (2013) present a 2 x 2 matrix where the problem and solution maturity can either be low or high. Thus, four types of research contributions are identified: invention, improvement, exaptation and routine design. Invention research contributions are "research in new and interesting applications where little current understanding of the problem context exists and where no effective artifacts are available as solutions" (Gregor and Hevner 2013). The research contribution of improvement research is to "create better solutions in the form of more efficient and effective products, processes, services, technologies, or ideas" (Gregor and Hevner 2013). Exaptation research contributions are "contributions where design knowledge that already exists in one field is extended or refined so that it can be used in some new application area." (Gregor and Hevner 2013). And last, routine design contributions are provided when "existing knowledge for the problem area is well understood and when existing artifacts are used to address the opportunity or question." (Gregor and Hevner 2013). However, routine design rarely presents new knowledge but can, in some cases, lead to surprising discoveries.

For DSR, the evaluation of an artifact is crucial in the creation of knowledge and is essential in improving artifacts often done as a part of a feedback loop. For evaluating an artifact, three aspects need to be addressed: quality, utility and efficacy (Hevner, March, Park, Ram, et al. 2004). The evaluation can take five different forms, which are depicted in Table 2.

Table 2. Design Evaluation Methods.

1. Observational	Case Study: Study artifact in depth in business environment
	Field Study: Monitor use of artifact in multiple projects
2. Analytical	Static Analysis: Examine structure of artifact for static qualities (e.g., complexity)
	Architecture Analysis: Study fit of artifact into technical IS architecture
	Optimization: Demonstrate inherent optimal properties of artifact or provide optimality bounds on artifact behavior
	Dynamic Analysis: Study artifact in use for dynamic qualities (e.g., performance)
3. Experimental	Controlled Experiment: Study artifact in controlled environment for qualities (e.g., usability)
	Simulation – Execute artifact with artificial data
4. Testing	Functional (Black Box) Testing: Execute artifact interfaces to discover failures and identify defects
	Structural (White Box) Testing: Perform coverage testing of some metric (e.g., execution paths) in the artifact implementation
5. Descriptive	Informed Argument: Use information from the knowledge base (e.g., relevant research) to build a convincing argument for the artifact's utility
	Scenarios: Construct detailed scenarios around the artifact to demonstrate its utility

Source*: Hevner et al. (2004)*

The evaluation methods presented in the paper by Hevner et al. (2004) provide little guidance in choosing the right evaluation approach. To address this issue, Pries-Heje, Baskerville, and Venable (2008) present a framework for selecting methods and metrics for evaluating DSR. The framework asks three questions about *what*, *how* and *when* an artifact is evaluated. The *what* question refers to whether the artifact is a design process or a design product. The *how* question addresses whether the artifacts have been evaluated in a naturalistic or artificial environment. Naturalistic evaluation refers to being evaluated in an environment of real people and real systems to solve real problems (Pries-Heje, Baskerville, and Venable 2008). Artificial evaluation refers to the opposite environment, consisting of unreal users, unreal systems, or unreal problems (Pries-Heje, Baskerville, and Venable 2008). Consequently, artificial evaluations may not prove useful in a naturalistic context, where naturalistic evaluations guarantee a better fit to reality and are "the real proof of pudding" (Pries-Heje, Baskerville, and Venable 2008). The *when* evaluation addresses the issue of at what time the evaluation was conducted, i.e. before or after the construction of an artifact. These are referred to as ex ante and ex post evaluations, respectively. The evaluation of the research rigor is based on the metrics mentioned in this section and is described and discussed in section 3.4.2.

3.4. Research methodology

Having discussed the selection of research form and the role of constructing and evaluating artifacts relevant and rigorous for both an academic and practical audience, this section will present the thesis research methodology.

The research methodology has been designed to address the research objectives of this thesis. Thus, the first part of the section presents the research objectives, the supporting research questions, and how they are related to each other and related to the appended articles of this thesis. Next are the relationships between the articles described, followed by a description of the structure and methods used in chapters 4, 5 and 6. This chapter concludes with a description of how the research objectives will be evaluated.

3.4.1. Overall research design and research objective

The research objectives were identified in section 2.5, which led to the formulation of two research objectives:

Objective 1: *To identify the value mechanisms at the intersection of value discovery and value creation by integrating analytics with EIS*

Objective 2: *To create an approach based on the value mechanisms in the intersection of value discovery and value creation by integrating analytics with EIS.*

To address these research objectives, an overall research design is proposed, which is presented in *Figure 9*.

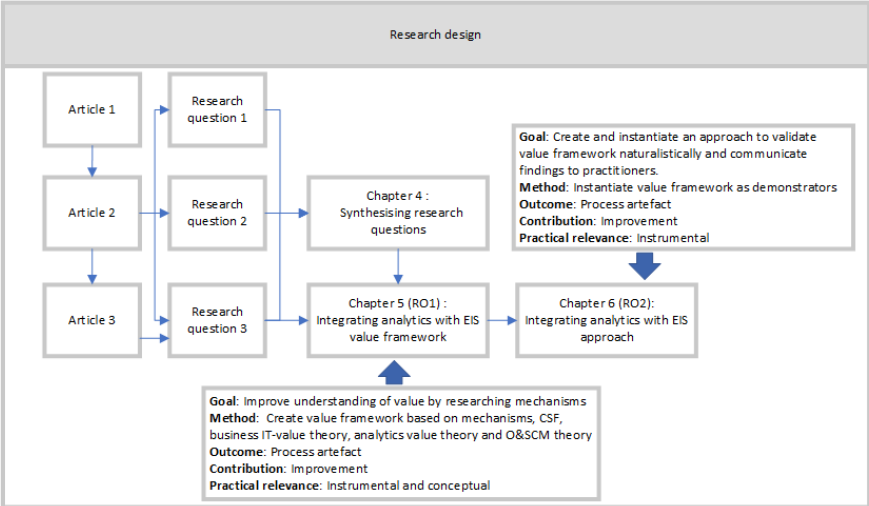

Figure 9. Overall research design.

The research design proposes three supporting research questions for addressing the first research objective, which are:

Research Question 1*: What is the state of the art of integrating analytics and EIS?*

Research Question 2*: What are future areas of research for integrating analytics and EIS?*

Research Question 3*: What are the mechanisms to integrate analytics and EIS for increased value discovery, analytic value intersection, and value creation?*

The purpose of the first research question is to build a rigorous baseline from which the research of this thesis can be based. Additionally, when reviewing the academic knowledge base, future areas for research are identified as part of research question 2. The last research question addresses the identification of mechanisms for integrating analytics and EIS from both a practical and an academic perspective. The mechanisms are identified as part of addressing the first two research questions and by researching in a practical environment using the construction and deployment of an analytic artifact via an ADS methodology on a case at Arla Foods. Addressing these research questions enables the possibility of answering the first research objective, where mechanisms are identified from both a practical and academic perspective. While the first research objective was researched both from a practical and academic perspective, it does present some limitations that need to be addressed. First, there is a fairly limited number of academic articles that were relevant for identifying mechanisms for the creation of value of integrating analytics and EIS. Additionally, as viewed from the perspective of a critical realist, the research conducted in one *real* environment does not reflect the whole *actual* environment. Consequently, there is a need to first compare and synthesise the findings from articles 2 and 3 (chapter 4), which set the baseline for extrapolating the findings related to the identified mechanisms for increased value output for value discovery and creation and the analytic intersection. The synthesised findings in the form of mechanisms will be further processed to supplement the identified mechanisms in the form of CSF, which are easier to apply and are more operationalisable. The mechanisms and CSF will be used to construct a value framework for integrating analytics with EIS in chapter 5, together with big data SCM value theory, IT business value theory, analytics value theory, and O&SCM theory. The value framework has two purposes: One, the framework addresses the first research objective, linking value and mechanisms of integrating analytics, O&SCM, and EIS. Two, the framework is used as the foundation for addressing the second research objective, which is presented in chapter 6. The mechanisms identified in the value framework are used to construct an approach, which shows how to operationalise the value framework from an IT perspective using current available technologies and methods. Further, the approach is used to create instances from an exploratory, exploitive and ambidextrous analytical value process perspective. The reason for creating an approach in the form of an instantiation is to present testable propositions of the proposed addition to the kernel theory, i.e. the value framework, as recommended by Gregor and Hevner (2013). By doing this, the research is more likely to become explainable, precise and resultingly more trusted (Gregor and Hevner 2013). Further, by presenting the mechanisms of value generation in the form of an instantiation using current technologies and methods, the research will be more actionable for practitioners, as recommended by Jonsson and Holmström (2016). Additionally, will two demonstrators be presented that show how the proposed approach can be used in a demand planning and manufacturing case. Demonstrators in this thesis are understood as a demonstration of the use of the proposed approach and value framework. Practically, this entails that the demonstrators can be seen as instantiations of the approach and identified mechanisms. The outcomes of the research are process artifacts that present how to generate value for exploratory, exploitive and ambidextrous organisations in relation to the use of analytics in O&SCM companies. The process artifacts can be regarded as conceptual and instrumental contributions. In summary, this thesis both constructs and uses process artifacts to identify, explain and validate the mechanisms for the creation of value in the intersection between value discovery and value creation. The value framework identifies and explains the mechanisms, where the approach is an instantiation of use, which can itself be seen as a mechanism. The demonstrators are instantiations of the approach, which naturalistic evaluates the findings of the thesis.

3.4.1.1 *Relationship between the articles*

The purpose of the three articles is to address the first research objective, where article 1 and article 2 are part of a literature review, and the third article presents a case of constructing and deploying an analytical IT artifact at Arla Foods. The literature review is presented in article 2, which makes use of a mixed-method methodology. The mixed-method methodology is developed and presented in article 1, where it was found that it was difficult to do a literature review within the research themes of analytics, EIS and O&SCM, as the keywords within the fields are ill-defined and mean different things in different contexts. The search of articles for the literature review returned more than 700 articles, which was deemed too much to manually review. Thus, a smart literature review methodology was developed in article 1, which combines the use of the machine learning method topic modelling with a structured literature review methodology. Using the developed methodology, the papers were grouped into related topics, where the relevant topics for the literature review were reviewed using a structured literature review approach.

Article 3 constructed and deployed an IT artifact in a manufacturing setting in two dairies at Arla Foods, using an ADS methodology. The construction and deployment made use of practical knowledge from the author, blogs, practitioners at Arla Foods, and from the literature review in article 2.

3.4.1.2 *Chapter 4 – Research summary*

The purpose of the research summary is to summarise the findings on value mechanisms from articles 2 and 3. The summary is presented in the form of two tables which highlight the research objective of the articles, the methods used, conclusions and, in the case of article 2, future research areas.

The tables are then synthesised by comparing whether findings have been observed in article 2, article 3, or in both articles, presented in a new table. The reason for synthesising the findings is to evaluate the generalisability of the findings by comparing observations from a real environment with the academic knowledge base. The findings of the articles are related to the somewhat vague term competitiveness used in the articles. The new synthesised table groups the findings into four groups: competitive prerequisites, competitive enablers, future research agenda, and additional findings. As the groupings are based on the term competitiveness, the findings are converted into a more process-oriented CSF related to value discovery, value creation, and the analytic intersection. The output of this section is used as a foundation for constructing the value framework in chapter 5. While the section does address the first research objective, it does not do so sufficiently, as there were not many academic papers directly relevant for the identification of value mechanisms, and the fact that the practical research was conducted in only one environment. Thus, there is a need to compare the findings with the kernel theories from the knowledge base to construct the value framework, which is done and presented in chapter 5.

3.4.1.3 *Chapter 5 – Integrating analytics and EIS value framework*

The purpose of chapter 5 is to construct a framework that defines *how* value can be created by the use of analytics. For this, the research framework presented in chapter 2, will form the basis for how to understand the creation of value by integrating analytics with EIS. However, this must be formalised and grounded in kernel theories from the knowledge base (Gregor and Hevner 2013). Thus, a value framework is constructed combining the research framework, the findings from chapter 4, the big data SCM value framework (Brinch 2018), IT business value theory, analytics value theory and O&SCM theory. Consequently, the framework combines the concepts, mechanisms and interrelations of EIS, O&SCM, and analytics identified in the attached articles with theories from the knowledge base. The value framework is considered to be the main answer to the first research objective. Additionally, the value framework presents an *improvement* to the value framework by Brinch (2018) by specifying the mechanisms of value generation between value discovery and value creation. Furthermore, the value framework presents a more nuanced view of value and analytical maturity than the framework proposed by Gartner in *Figure 1*.

The output of this chapter is considered a process artifact that presents value-generating perspectives on exploratory and exploitive processes. Thus, the chapter first presents the concepts of exploration and exploitation related to O&SCM analytics and discusses how to achieve balance between the two as an ambidextrous organisation. Then kernel theory about O&SCM analytics value mechanisms is presented and discussed. This is compared to the concept of exploration and exploitation, which results in a presentation and discussion of O&SCM analytics decoupling points. The decoupling points are used for balancing exploration and exploitation in the final value framework. Next are O&SCM IT value mechanisms from the kernel theory discussed, with a special focus on IT business value.

The framework is centred on the analytic process, which is structured by the use of the analytic process framework CRISP-DM, and related to the value definitions of value discovery, analytic value intersection, and value creation. The framework is also supported by presenting the CSF and mechanisms identified in the research of this thesis and by presenting the concept of IT capabilities within the research theme of IT business value. Consequently, the framework consists of three parts: value discovery, analytic value intersection, and value creation. For each part, the framework presents how to balance exploratory and exploitive processes, which is supported by presenting the mechanism, CSF and IT capabilities for each value part.

It is believed that the value framework brings clarity for how to create value by the use of analytics in the O&SCM and the EIS research domains, which is relevant for both academics and practitioners. The evaluation of the value framework is intertwined with chapter 6, which is why a discussion of evaluation is presented in section 3.4.2.

3.4.1.4 *Chapter 6 – Integrating analytics and EIS approach*

The purpose of chapter 6 is twofold. First, the chapter will be used to create an approach based on the value framework, which instantiates the value framework by using currently available technology and methods aiding both practitioners and academics in making use of the identified value-generating mechanisms. The second purpose is to evaluate the value framework in a real environment, where the approach of this chapter is used in two demonstrators in a demand planning and manufacturing case, respectively.

The approach is constructed based on the identified CSF and mechanisms of the value framework. These mechanisms and CSF will be used to identify requirements for the construction of the approach. The focus of this thesis has taken on an IT process perspective, and as such does the approach reflect this perspective. The approach will make use of current technological solutions and methods to address the needs for exploratory, exploitive and ambidextrous analytics integration with EIS. The approach is aimed to be applicable for any organisation, and thus some level of configuration is required for a company to operationalise the approach.

However, to present how the approach is meant to be used, three instantiations are presented for an explorative, exploitive and ambidextrous approach. The instantiations communicate how and where data are stored and managed, as well as where data are processed into analytical artifacts and how these artifacts can be deployed and integrated with a business workflow.

Last, the approach is used to build two demonstrators, which presents how the approach can be used. The demonstrators are conducted at Arla Foods, where the first demonstrator is a case where analytics is used to improve the demand planning process of their SAP APO system, and the second demonstrator is a case where an analytical artifact is constructed and deployed with an MES.

The demonstrators present how the use of analytics can improve the current use of EIS by integrating analytical artifacts into a company's business processes. The demonstrators therefore act as a validation of the approach, where the approach has been validated academically from the rigorous construction of the value framework, and is practically validated by presented two demonstrations of use in a real environment. Essentially, the approach and demonstrators communicate how the proposed integration of analytics into O&SCM business processes and EIS is an improvement over current solutions.

3.4.2. Evaluation

Having described the overall research design, the evaluation methods will be described in the following section, which evaluates the research objectives, presented in *Table 3*. The evaluation of the research objectives depends on each other, e.g. the usability and usefulness of the value framework are evaluated by the instantiation and demonstrators presented in chapter 6. The evaluation of the research is presented sequentially, as depicted in the table, starting with a discussion on the topic of using process or product artifact, and ending with presenting the criteria for evaluating the research. The evaluation regarding addressing the practical vs. academic relevancy is discussed in section 7.

Table 3. Evaluating Research Objectives.

Research Objective	Design process artefact or design product artefact	Contribution type	Generalizability level	Naturalistic or artificial	Ex ante or ex post	Practical relevance	Criteria
1. To identify the value mechanisms in the intersection of value discovery and value creation by integrating analytics with EIS.	Process	Improvement	Level 1 & 2	Naturalistic	Both	Instrumental & conceptual	Usefulness, usability, and improvement over current solutions
2. To create an approach based on the value mechanisms in the intersection of value discovery and value creation by integrating analytics with EIS	Process	Improvement	Level 1	Naturalistic	Both	Instrumental	Usefulness, usability, and improvement over current solutions

3.4.2.1 *Design process artifact or design product artifact*

To be able to address the research objectives in a design science manner, either a product artifact or process artifact is sought (Pries-Heje, Baskerville, and Venable 2008). The two research objectives are addressed and evaluated as process artifacts. The outcome of the first research objective is a value framework that is based on the knowledge extracted from the knowledge base and by the construction and deployment of analytical artifact products. The purpose of the first research objective is to identify general mechanisms for integrating analytics with EIS, applicable for different companies in different contexts. Consequently, addressing the first research objective entails a process artifact, as the construction of a product artifact in most cases addresses a problem for a specific organisation.

The second research objective is also a process artifact, based on the same arguments as the first research objective. However, the process artifact is different where the process artifact is presented as an instrumental contribution, and the first research objective is addressed as a combination of instrumental and conceptual contribution. It can be argued that both research objectives make use of product artifacts, as artifacts are constructed for both research objectives. As such, addressing the research objectives could also have been done using a product artifact approach. However, it has been chosen to construct process artifacts, as it is believed to be easier to use and generalise for both academics and practitioners.

3.4.2.2 *Contribution type*

The contribution types can be improvement, invention, routine design, or exaptation (Gregor and Hevner 2013). The contribution type for both research objectives is seen as an improvement. The first research objective improves and extends the knowledge of the mechanisms for integrating analytics with EIS and O&SCM regarding value. The outcome is believed to contribute to a better understanding of how to generate value when data is processed and analysed to generate better insights and actions in the field of O&SCM.

The contribution type for the second research objective is also seen as an improvement, though it can be argued as speculative. The improvement is presented as an improved understanding of how to apply the identified mechanisms in a naturalistic environment. The research is therefore easier to communicate to practitioners, but lacks academic rigor compared to the first research objective. It is, however, of the author's opinion, that the second research objective aids in balancing academic and practical relevance. It could also be argued that the contribution type of addressing the second research objective is exaptation, as the knowledge and practices from analytics and IT are adopted in the business workflow of O&SCM companies. However, it is the view of the author that O&SCM, analytics and EIS are already being used together and have been for decades. Therefore, even though many of the tools and methods of analytics have not been applied within the O&SCM and EIS domains, integrating these tools and methods must be seen as an improvement to an already existing process. The improvement comes from the application and instantiation of the value framework and therefore brings a better understanding and evaluation of the identified mechanisms.

3.4.2.3 *Generalizability level*

The generalisability of DSR can be done on three levels (Gregor and Hevner 2013). The first research objective makes use of level 1 and level 2. The first level of generalisability is addressed by the construction of analytical artifacts as instances in the environment of Arla Foods. The research therefore presents findings of which mechanisms were identified in the construction and deployment of analytical artifacts in a real environment. These findings are evaluated with kernel knowledge from the knowledge base, which is used to abstract the findings to a conceptual level, as a value framework.

The second research objective presents an instantiation of the value framework at level 1, where the methods and models of the research theme of analytics are used in the research themes of O&SCM and EIS. The second research objective therefore contributes with research that is applicable and operational for both academics and practitioners, which hopefully aids in closing the gap between practice and promise.

3.4.2.4 *Naturalistic or artificial*

There are two environments where research can be evaluated, either in a naturalistic environment (real) or artificial environment (unreal) (Pries-Heje, Baskerville, and Venable 2008). Both research objectives are evaluated in a naturalistic environment, where the development and construction of the value framework is based on naturalistic observations, and the instantiation is evaluated with two demonstrators applied in a real environment.

3.4.2.5 *Ex ante or ex post*

The process artifacts have both been evaluated before and after construction. The artifacts have continuously been evaluated for academic and practical relevance and rigor during each of their iterations. The discussion in this section and sections 5 and 6 can be seen as the final evaluation of the process artifacts.

3.4.2.6 *Practical relevance*

Practical relevance can be evaluated in three ways: as instrumental, conceptual or legitimate (Nicolai and Seidl 2010). The first research objective provides both instrumental and conceptually relevant research, as both technological rules are provided, and a framework that uncovers contingencies. The second research objective contributes with instrumental relevant research, where an approach is proposed in the form of an instantiation, which operationalised the value framework. The research therefore presents a general understanding of *how* to generate value from analytics in the O&SCM and EIS research domains and operationalises it to be easily applicable for a capable practitioner.

3.4.2.7 *Criteria*

The criteria for evaluation are based on the evaluation of contribution types and are categorised as quality criteria, which are dependent on the goal of the research (Gregor and Hevner 2013). The evaluation should preferably be grounded in kernel theories from the knowledge base (Gregor and Hevner 2013). Both research objectives are contributing with *improvements* to current research, and consequently, the evaluation criteria for both are the same. The evaluation criteria for both research objectives are their usefulness, usability and the research need to show how the artifacts is an improvement compared to current solutions. Usefulness evaluates if the artifact was able to address the predetermined purpose of the artifact, and usability evaluates to what degree a person can make use of the artifact. The improvement over current solutions is evaluated by comparing “positive changes in efficiency, productivity, quality, competitiveness, market share, or other quality measures, depending on the goals of the research” (Gregor and Hevner 2013).

The evaluation of the two process artifacts that address the two research objectives are evaluated individually and together. Regarding usefulness and usability, the process artifacts must identify the mechanisms for value generation by the use of analytics in the O&SCM domain and make it easily consumable and applicable for both academics and practitioners. The value framework is seen as an easily consumable process artifact for academics to apply and make use of for other related research. The value framework is presented as a visualisation, which presents the relationships between the value generating mechanisms, CSF, analytic process steps, IT capabilities and analytic value type. The value framework further presents general mechanisms that capable practitioners can make use of and integrate into their specific organisation. However, applying the value framework to something operational requires practitioners to know about many research domains. This is something that cannot be assumed that companies possess, which is why the value framework is operationalised as an approach and instantiated. In addition to aiding practitioners with how to use the value framework, instantiation is also used to evaluate the usefulness of the value framework by applying the value framework onto two demonstrators. The usefulness of the value framework is effectively evaluated from an academic perspective by grounding the construction of the framework on kernel theory, and the practical relevance is ensured by applying the process artifacts to two demonstrators in a real environment.

The final evaluation examines how the process artifacts provide improvements over current solutions. From an academic perspective, the process artifacts present new understandings of the value generating mechanisms within the use of analytics in O&SCM, which so far has been missing. The process artifacts also show how to balance the exploratory and exploitive analytic processes, which is also missing from current competing solutions. From a practical standpoint, the process artifacts present how to make use of and integrate the use of the analytical open-source workflow with the rigid BPM of EIS. The improvement that the process artifacts provide is exemplified by the two demonstrators, where both a demand planning process and manufacturing process are improved by providing new insights and actions that current EIS solutions cannot provide.

In summary, this thesis aims to increase the understanding of how to create value through the use of analytics by integrating analytics with EIS for the O&SCM company. To do so, a process artifact is constructed as a value framework, which is based on the identified mechanisms and CSF in the appended articles, IT business value theory, analytics value theory, and O&SCM theory. The value framework is then applied and validated in a naturalistic environment by constructing an approach, as a process artifact, based on current methods and technologies, which is instantiated into two demonstrators.

Chapter 4. Research summary

This section will dissect the appended articles and provide a summary of the findings and relate that to the value discovery, analytic intersection, and value creation perspectives. As specified in the previous section, the research findings have been generated from two perspectives: the knowledge base through a literature review and from researching within a relevant environment creating prescriptive knowledge. Consequently, the purpose of this section is to combine the findings from the two perspectives to address the research objectives of this thesis.

The findings in this section are summarised into three overviews. The first overview, section 4.1, presents the findings of article 2 and article 3 as a summary in two tables. The tables present the research objective of the individual article, the methodology used, a summary, the conclusions from the article, and article two has additionally a section on future research areas.

The second overview, presented in section 4.2, is a synthetised version of the two tables in section 4.1. The comparison of the articles is done according to the research themes of the articles, which are competitive prerequisites, competitive enablers, future research agenda, and additional findings. The outcome is a table visualising whether the findings have been observed in the literature review, the case work, or both instances. It should be noted that the articles do not specifically define value but instead use the term competitiveness. While the articles fail to define value, competitiveness in the articles is mostly related to the value discovery, analytic intersection, and value creation processes defined by Brinch (2018).

While the synthesised table does present an overview of findings for integrating analytics with EIS, it is not operational or in direct relation to the value discovery, analytic intersection, and value creation perspectives. Thus, a third overview is presented in section 4.3, where CSF are identified in relation to value discovery, the analytic intersection, and value creation. The CSF will be used as a foundation for constructing the value framework in chapter 5.

4.1. Summary of articles

This section presents the summaries of articles 2 and 3 in *Table 4* and *Table 5*, respectively.

Table 4. Summary of Article 2.

Article 2: Enabling Supply Chain Analytics for Enterprise Information Systems: A Topic Modelling Literature Review and Future Research Agenda
Research Objective:
Literature review and future research agenda for the research themes analytics, supply chain management, and EIS in relation to competitive enablers.
Method:
Mixed-method two-stage methodology, combining topic modelling methodology (based on article 1) with a structured literature review
Summary:
The article reviews 650 papers by first grouping the papers into twenty topics using topic modelling, where three out of the twenty topics were evaluated as relevant to the research objective. A systematic literature review was conducted on the three topics containing seventy-five papers, which were further grouped into the research themes of 'ERP Implementation and Post-implementation', 'EIS and Analytics', 'Data and Analytics', 'Data and System Integration', 'Literature Review' and 'Networked Manufacturing and ERP systems'. The review led to the following conclusions and future research agenda.
Conclusions:
• **Critical Factors** - Critical factors for implementation success: top-management support, user skill/training, performance evaluation, context-dependent configuration, implementing the project as a business project, and having a large budget (Asmussen and Møller 2020) - Important contextual factors: country, industry, implementation life cycle, culture and maturity (technology, people, systems) (Asmussen and Møller 2020)

- Organisational benefits are realised by creating a functional fit and ensuring good EIS implementations (Asmussen and Møller 2020)
- Integrating data with IT systems increases data usage (Asmussen and Møller 2020)

- **Analytics in Enterprise Information Systems**
  - EIS improves decision-making quality and speed.
  - Most companies use descriptive analytics on aggregated data.
  - Several researchers recommend moving towards real-time analytics.
  - Dynamic supply chains should be supported by human-centric IT systems capable of quickly processing transactional and operational data.
  - Most researchers recommend standardising data management using frameworks, such as ISA-95.
- **Analytics application**
  - OR methods are rarely used in companies, but researchers recommend companies to make use of the OR methods.
  - Analytical applications should be useable by non-experts and present results to relevant end users.
  - Companies are struggling with developing explicative models that support real-time data processing.
  - Analytic applications cannot support coordination between workers, such as cooperation between high-level planners and schedulers.
- **Data requirement and acquisition**
  - Low research interest in data acquisition for use in analytics.
  - Data is proposed to be managed differently based on management layers, such as time horizon, level of detail, external/internal orientation, and decisions (judgemental/rules/analytic) (Asmussen and Møller 2020).
  - Big data and real-time data processing enable better transparency and optimisation opportunities for supply chain processes.
- **Enterprise Information Systems**
  - ERP is seen as a competitive necessity (facilitates greater efficiency, flexibility, reporting abilities, and better decision support).
  - MES is identified as a competitive differentiator due to the potential high volume of data to be recorded and processed in real time.
  - MES enables detailed planning of individual products, better logistic coordination, as well as high degrees of traceability (Asmussen and Møller 2020).
  - Real-time data enable better information sharing and responsiveness and enable the handling of low-volume, high-variety orders.
  - Real-time data recorded via IoT is an enabler for manufacturing big data.
  - Introducing new IT system landscapes can introduce a new business model or vice versa.
  - All EIS frameworks proposed were conceptual.

Future Research Agenda:
Context - There is a lack of research on contextual factors impacting the use of analytics in SCM. This is an important research area, as there are no one-size-fits-all solutions for analytical implementation, use or integration.   **Cross-functional analytics** - There is a lack of cross-functional analytics research, where most research is done within a specific supply chain function. - Most research within the area is conceptual.   **Cross-planning level analytics** - The literature review found no research on integrating the use of analytics across planning levels, i.e. operational, tactical and strategic time horizons.   **Implementation and assimilation of analytics in EIS** - Successful implementation and assimilations of EIS have sufficient degrees of IT technical, supply chain, and managerial capabilities. - Research on implementing and assimilating analytics with EIS is scarce.   **Analytics and Big Data for SCM** - Researchers have not addressed how specifically analytics enables better supply chain planning for increased competitiveness. - It is unknown which data are relevant for analytical application for different functions of the supply chain and how the data should be processed by cleaning and aggregating data, for example. - Empirical research on how big data enables better planning and execution regarding increased competitiveness is missing.   **Managerial aspects of analytics** - None of the papers reviewed dealt with the managerial aspects of analytics, which should be researched.   **Data and system heterogeneity** - Most companies have heterogeneous data systems which must be integrated for the successful use of analytics. However, there is a lack of research on integrating analytics with these heterogeneous systems. - There is further a lack of understanding of how to integrate the use of heterogeneous data into O&SCM analytics. Sources of these heterogeneous data are IoT, and external structured and unstructured data. - The MES system is identified to be at the heart of many of these challenges and thus presents a good starting point for researchers.

- Additionally, the APS system has been identified to have great benefits in integrating with analytics applications. - Scaling analytical solutions is a prerequisite for generating a competitive advantage; however, to do so requires a solution that can scale based on heterogeneous data and systems.

Source: Asmussen and Møller (2020).

Table 5. Summary of Article 3.

Article 3: Design and deployment of an analytic artifact – investigating mechanisms for integrating analytics and MES
Research Objective:
Investigate the mechanisms of integrating an analytic artifact with a manufacturing execution system
Method:
Action Design Science
Summary:
The article investigates the mechanisms of integrating an analytical artifact with an MES system at a dairy company. The analytical artifact is constructed as a single analytical product consisting of three parts: a predictive model, a prescriptive model, and a visualisation toolbox using explainable AI. The artifact was constructed at a single manufacturing site and deployed at the same site, as well as deployed at an additional manufacturing site.
Conclusions:

- An analytical artifact can be constructed solely based on a business problem, i.e. not considering the specific context of the manufacturing site.
  - Consequently, an analytical artifact can be constructed without considering the IT systems, processes, tasks and products of the manufacturing site (Asmussen and Møller 2020)
  - This indicates that an analytical artifact can be constructed to be scalable across heterogeneous manufacturing sites.
- Data must be aggregated and traceable on a production unit level for diagnostic, predictive and prescriptive analytics.
- Two barriers to constructing the artifact were identified:
  - Data Barrier (enabling descriptive, diagnostic, predictive and prescriptive analytics).
  - Analytical capability barrier (enabling predictive and prescriptive analytics).
- Analytic artifact integration is different from EIS integrations due to:
  - Implementation project is significantly smaller in scope.
  - Faster to integrate.
  - Requires a different skill set (analytical, IT, data management capabilities, and domain knowledge).
  - Construction and deployment do not interrupt daily operations.
  - Usually constructed for a specific business issue instead of purchasing a standard software product from an external vendor.
- Analytic artifacts can be built using only open-source software.
- Different human capabilities are needed for different phases of constructing an analytical artifact:
  - Understanding business and data requires domain knowledge and analytical capabilities.
  - Data preparation and modelling require data management, IT and analytical capabilities.
  - Deployment requires IT capabilities and can be treated as a regular IT integration project.
- An analytical artifact can be constructed by a single data scientist, but it is recommended to utilise a team instead, as a data scientist can become a bottleneck.

Source: Asmussen, Jørgensen, and Møller (2020).

4.2. Synthesising the findings of the articles

This section presents the findings from both articles in a synthesised summary, which visualises and highlights the findings related to being observed in the knowledge base, in the case work, or observed in both instances. The findings are grouped according to the themes of the articles, which are competitive prerequisites, competitive enablers, future research agendas, and additional findings. The findings are further related to the themes of the thesis: EIS, analytics and general findings. The overview is presented in *Table 6*.

Table 6. Joint Summary of Research Articles.

	EIS	Analytics	General Findings	Observed in:
Competitive Prerequisite	ERP	Descriptive and diagnostic analytics		Both papers
	EIS implementation and assimilation critical success/failure factors	Models needs to be human centric and relevant		Paper 2
		Overcomming data barrier		Paper 3
Competitive Enabler	MES	Predictive & prescriptive analytics	Context dependent configuration	
	APS	Big Data Analytics	Managing analytics & EIS implementation and integration	
	Mananging heterogeneous data	Scaling analytics	Human capabilities (IT, data management, analytical, and domain	
	Mananging heterogeneous IT-systems	Real time analytics		
	Support for fast processing of transactional and operational data	Overcomming analytical capability barrier		
Future research agenda	Integrating MES and analytics	Cross-functional analytics	Managerical aspect of integrating analytics and EIS	
		Cross-planning level analytics		
		Operationalised frameworks for integrating analytics with EIS for increased competitivess	Assimilation of analytics	
		Data requironments		
Additional Findings	EIS is good at managing BPM, but not for advanced analytics	A generic analytical product can be constructed to be useable for multiple heterogeneous manufacturing sites	Analytic artefact integration is very different from EIS implementations	
		Analytic artefacts should be constructed by a team	Analytic artefacts can improve current execution and planning processes	
		An analytic artefact can be constructed and deployed at a fairly low budget	EIS lacks access to advances analytical methods	
		Analytical artefacts which learn on data are able to be scaled	Analytic artefacts can be constructed and deployed quickly given specific data requirements are met.	
		An analytic artefact can be constructed without considering IT-systems, processes, task, and products.	Different capabilities are required for the construction and the deployment of an analytic artefact.	
		CRISP-DM was a good methodology for structuring the construction of an artefact	Data must be traceable and aggregated on production unit level to enable analytics at a manufacturing site.	

The table shows a total of thirty-eight observations, where fourteen of the observations have been identified both in the literature review and in the case work. These fourteen observations are regarded as relevant for both practitioners and academics, as they have been identified in both an academic and industrial environment. An additional fourteen observations have been identified in the literature review, where many of the observations are relevant to environments other than the case work, i.e. environments not related to manufacturing and MES. Finally, ten observations have been made in the case work, which have not been identified in the literature review. These observations are regarded as prescriptive knowledge, that is, the creation of new knowledge. It should be noted that some future research issues identified in the literature review have been addressed in the case work, specifically, the research agenda of integrating analytics and MES and identifying data requirements for manufacturing analytics.

The table enables the possibility to create an overview of the competitive prerequisites, as well as competitive enablers for integrating analytics and EIS. Additionally, important unaddressed research areas can be identified to be used as a foundation for future research.

The competitive prerequisites for integrating analytics with EIS are:

- An implemented and assimilated ERP system
- Descriptive and diagnostic analytics
- Making analytic models human-centric and relevant for end users
- Overcoming the data barrier

The competitive enablers for integrating analytics with EIS are:

- Integrating analytics with other EIS modules such as MES or APS
- Integrating predictive and prescriptive analytics
- Managing heterogeneous data and IT systems
- Support for real-time analytics, which entails support for fast processing of operational and transactional data
- Creating analytic artifacts that scale well
- Overcoming the analytical capability barrier
- Creating analytic artifacts that fit with the context
- Having access to sufficient data management, IT, analytical capabilities, and domain knowledge
- Managing analytics implementation and integration per the identified critical factors

Future research areas of integration analytics with EIS are:

- Cross-functional analytics
- Cross-planning level analytics
- Operationalised frameworks for integrating analytics with EIS for increased value discovery, analytic intersection, and value creation
- Data requirement for analytic artifacts in non-manufacturing applications
- Managerial aspects of integrating analytics and EIS
- CSF for implementing and assimilating analytical artifacts into an organisation

Some additional findings that cannot be directly related to competitiveness were observed, which are presented below.

The use of EISs provides many benefits, especially regarding managing the business processes of a company. However, the most popular EIS solution providers rarely make available sufficient offerings within the analytics domain. The EIS offerings often lack access to advanced analytical methods and do not have the flexibility to customise the data and analytical model to a context-specific case.

It is possible to create analytic solutions that scale well, given that specific requirements are met. An analytic artifact can be constructed to address similar business problems across manufacturing sites, without considering the specific IT systems, work processes, tasks and products, given that the data requirements are met. For scaling analytic solutions in a manufacturing setting, the data must be traceable and aggregated on a production unit level. Further, enabling the scalability of the analytic artifact requires that the artifact is based upon the learning of data instead of the creation of purpose-built statistical models.

Additionally, the integration of analytic artifacts is greatly different from similar EIS projects. Analytic artifact construction and deployments can be done fairly quickly at a low cost, without interrupting daily operations. The construction of an analytic artifact is created using open-source software, where the enterprise data is processed into a model, which later is integrated into the business workflow of the company. The benefit of the open-source software is not that it can be obtained for free, but that it is continuously updated with the best performing analytical model developed, e.g. by OR researchers, and have the best analytics and data management frameworks. Essentially, by exploiting the use of open-source software, companies can improve their planning and execution processes to become more effective and/or efficient.

Finally, different capabilities are needed for the different phases of constructing and deploying an analytical artifact. The different capabilities are domain knowledge and analytical capabilities for aligning business and data understanding. Data management, IT and analytical capabilities in preparing the data and creating an analytical model, and finally, IT capabilities for deploying the artifact. Furthermore, while all phases could be done by one person, it is recommended to have a team conduct the entire process to avoid bottlenecks.

While this section presents a synthesised overview of the findings of the appended articles, it does so regarding a somewhat ill-defined concept of competitiveness. What is further needed is to relate the findings to value discovery, the analytic intersection, and value creation and make the findings operationalisable for constructing a framework for integrating analytics with EIS. Consequently, the following section will identify the CSF for value discovery, value creation, and the analytic intersection of integrating analytics with EIS.

4.3. Critical success factors for integrating analytics with EIS

CSF have been used extensively in the implementation and assimilation literature within the EIS domain, which have led to a good understanding of how to successfully implement EISs given different contexts. A summary of some of the most important CSF for EIS implementations are presented in Asmussen and Møller (2020). While the clarification of CSF for EIS implementation and assimilation have proven to be useful, both for academics and practitioners, the identification of CSF for integrating analytics with EIS have not received the same research interest.

CSF are defined as a limited number of factors that must be managed to obtain successful and competitive performance for an organisation (Rockart 1979). As such, the identification of CSF does not entail identifying all factors impacting a project, but instead relies on identifying a manageable number of factors, which will steer the project towards a successful direction. Consequently, the identification of CSF can transform the identified mechanisms of integrating analytics with EIS into a select few important factors, which can be used as the foundation to construct the value framework presented in chapter 5.

The CSF for integrating analytics with the EIS have been found by relating the findings in section 4.2 to the value discovery and value creation and the analytical intersection between the two. The results are presented in *Table 7*.

Table 7. CSF for Integrating Analytics with EIS Regarding Value Discovery, the Analytic Value Intersection, and Value Creation.

Critical Success Factors		
Value Discovery	**Intersection (analytics)**	**Value Creation**
Overcoming the data barrier	Human centric and end user relevant analytic models	Integrating analytic artefacts with EIS e.g. MES or APS
Managing heterogeneous data and IT systems	Scaling analytic artefacts	Having an implemented and assimilated ERP
Data management and IT capabilities	Overcoming the analytical capability barrier	
Support for fast processing of internal and external transactional and operational data	Fitting analytical artefact with a relevant business issue	
	Create analytic artefacts based on open source software	
	Use domain knowledge in analytic model	

These CSF should be taken into consideration when integrating an analytic artifact with an EIS. The CSF covers different perspectives, such as ensuring proper data and IT management, ensuring the right human capabilities are available, and making sure an analytical artifact is fitted to a relevant business problem. As analytic artifacts are used to support the business workflow by enabling better decision-making, successful implementation requires that the business workflow is well established and the underlying EIS has been properly implemented and assimilated.

Not all of these CSF are equally easy to address, where ensuring the right human capabilities can be addressed by hiring internal or external workers. On the other hand, ensuring a properly defined, implemented and assimilated business workflow system can be very costly and take several years to attain. Consequently, extracting value from analytics should only be the aim of a company, once the EIS foundation is well established.

While the identified CSF should steer analytic integration projects towards integration success, there are likely other factors that are as important as the ones identified. Specifically, the empirical research of this thesis has mainly focused on the manufacturing site of analytics, where other findings may be relevant for other parts of the O&SCM company. Thus, the next section presents a value framework incorporating the findings of this chapter with kernel knowledge from the knowledge base as recommended by (Gregor and Hevner 2013). Additionally, six future research areas which are not researched in the attached articles were identified, which will likely provide additional CSF for integrating analytics with EIS.

Chapter 5. Integrating analytics, O&SCM, and EIS value framework

This section builds on the research summary presented in the previous section and combines the findings with related works from the literature knowledge base. This section aims to improve the value framework proposed by Brinch (2018) by incorporating mechanisms of generating insight and actions from data into business processes through the use of analytics. The output of this section is a new value framework that extends the understanding of value in data, analytics, EIS and O&SCM by introducing the mechanisms for *how* to generate value. The proposed value framework is based on the research presented in the appended articles, analytics value theory, IT business value theory, and O&SCM theory.

The value framework from Brinch (2018) proposes that there are two analytical paths from value discovery to value creation, i.e. an exploration or exploitation path. The distinction between the two paths is taken from O&SCM theory, coined as the productivity dilemma (Benner and Teshman 2003), where exploration is a process that searches for new or improved solutions to organisational or marked issues, and exploitation is a process that utilises current organisational knowledge and skills (Levinthal 1991; Levinthal and March 1993). Companies have been trying for decades to find the balance between using resources to explore new opportunities and new ways of doing things and efficiently exploiting current resources (Adler et al. 2009). For more than a century, managers and operations researchers have argued and seen the benefits of making use of strict process templates to increase efficiency (Adler et al. 2009), originating with (Deming 1986; Taylor 1911). However, in recent decades, researchers have found that efficiency gains also come with heavy cost (Adler et al. 2009; Levinthal and March 1993). The cost comes from the lack of innovation and learning, which makes companies rigid and inflexible, which have resulted in turning companies who once were profitable, to not fit with a changing environment, to be brittle and in some instances collapse (Adler et al. 2009).

Few companies manage to find the balance between exploration and exploitation, into what is called an ambidextrous organisation, but some companies have succeeded, such as Toyota which “moves slowly, yet it takes big leaps” (Adler et al. 2009). Ambidextrous companies succeed by creating and separating exploratory units and exploitive units, where the exploratory units succeed by experimenting and creating small wins and losses frequently and exploitation units succeed by reducing variability and maximising efficiency (Adler et al. 2009). Thus, a truly ambidextrous organisation physically and culturally separates exploratory units and exploitive units and has different incentives, measures and management teams (Raisch and Birkinshaw 2008).

The value a company can extract from exploratory and exploitive processes depends on the type of environment the company is in. In stable environments, companies can focus on exploiting their resources, where in turbulent environments most value can be extracted from exploratory activities (Adler et al. 2009).

Historically, a big part of the improvement in O&SCM processes has been driven by technological development (Benner and Teshman 2003). Many view the use of analytics in O&SCM from that aspect, where analytics (technology) can be used to change and innovate company processes for better decision-making. Within the scope of applying analytics within O&SCM companies, most companies are facing a turbulent environment driven by the fast development of technologies and analytical methods. Consequently, it can be argued that for most companies, most value can be extracted from the exploratory processes, where once a more stable environment is found, companies need to shift their focus to exploitation. The adaptation of technologies into the O&SCM processes is mainly driven by the use of analytics and IT. Consequently, the next two sections will present the mechanisms for creating value in O&SCM analytics and business IT, which will lead to a presentation of a value framework.

5.1. O&SCM analytics value mechanisms

Fundamentally, analytics can create value either by providing value in learning, i.e. insights or knowledge, or provide value in use, often as an analytic product (Viaene and Van Den Bunder 2011; Larson and Chang 2016). Thus, the deployment of analytics is based on processed data intended to trigger decisions and actions (Bose 2009; Davenport and Harris 2017; Seddon, Calvert, and Yang 2010). The outcome of analytics is either consumed as part of an established business process, usually as part of an IT-BPM system, or consumed by a user (Herden 2019). The outcome is measured by the resulting business or process performance (Herden 2019). If the outcome of analytics is not consumed properly, by late or missed deployment or the analytic outcome leading to wrong conclusions, this leads to a lack of value and further prevents users from accepting and trusting the analytical output (Herden 2019). Consequently, actions or decisions are based on the transformation of data into consumable knowledge, either in an automated fashion or presented as consumable insights in the form of understandable decision support for users (Davenport and Harris 2007; Ross, Beath, and Quaadrgrass 2013; Bose 2009; Viaene and Van Den Bunder 2011; Barton and David 2012).

The analytics process is exploratory and experimental in nature, and the course of construction changes iteratively based on insights gained during the construction of an analytic artifact (Bose 2009; Viaene and Van Den Bunder 2011; Marchand and Peppard 2013; Larson and Chang 2016; Carillo 2017). The analytics process usually starts from a business problem, identified by end users, ensuring fit to a business process and user needs (Herden 2019). Next, data is collected, prepared and analysed to create a model that solves a business problem (Herden 2019; Provost and Fawcett 2013; Leventhal 2015; Shearer 2000). The model is then deployed and continuously maintained to support the use of the model (Larson and Chang 2016; Asmussen, Jørgensen, and Møller 2020).

The analytical models can be complex to construct and may require reconstruction or retraining over time as data changes. Thus, there is a great demand for technical capabilities for applying analytical methods and for managing data, which is why it is recommended to have a cross-functional team mixing workers with domain knowledge and technical knowledge (Davenport and Harris 2017; Viaene and Van Den Bunder 2011; Marchand and Peppard 2013; Larson and Chang 2016; Seddon, Calvert, and Yang 2010; Berinato 2019).

There are many uses of analytics in an O&SCM company, where Souza (2014) presents some examples of the application of analytics for different functions based on the SCOR framework, in *Table 8*.

Table 8 - Examples of use of analytics based on the SCOR framework

SCOR Domain	Source	Make	Deliver	Return
Activities	Order and receive materials and products	Schedule and manufacture, repair, remanufacture, or recycle materials and products	Receive, schedule, pick, pack, and ship orders	Request, approve, and determine disposal of products and assets
Strategic (time frame: years)	• Strategic sourcing • Supply chain mapping	• Location of plants • Product line mix at plants	• Location of distribution centers • Fleet planning	• Location of return centers
Tactical (time frame: months)	• Tactical sourcing • Supply chain contracts	• Product line rationalization • Sales and operations planning	• Transportation and distribution planning • Inventory policies at locations	• Reverse distribution plan
Operational (time frame: days)	• Materials requirement planning and inventory replenishment orders	• Workforce scheduling • Manufacturing, order tracking, and scheduling	• Vehicle routing (for deliveries)	• Vehicle routing (for returns collection)
Plan	Demand forecasting (long term, mid term, and short term)			

Source:(Souza 2014).

Additionally, Waller and Fawcett (2013) present examples of (big) data in the supply chain (*Table 9*), which can be used to facilitate predictive analytics.

Table 9 - Examples of O&SCM (big) data

Type of data	Volume	Velocity	Variety
Sales	More detail around the sale, including price, quantity, items sold, time of day, date, and customer data	From monthly and weekly to daily and hourly	Direct sales, sales of distributors, Internet sales, international sales, and competitor sales
Consumer	More detail regarding decision and purchasing behavior, including items browsed and bought, frequency, dollar value, and timing	From click through to card usage	Face profiling data for shopper identification and emotion detection; eye-tracking data; customer sentiment about products purchased based on "Likes," "Tweets," and product reviews
Inventory	Perpetual inventory at more locations, at a more disaggregate level (e.g., style/color/size)	From monthly updates to hourly updates	Inventory in warehouses, stores, Internet stores, and a wide variety of vendors online
Location and time	Sensor data to detect location in store, including misplaced inventory, in distribution center (picking, racks, staging, etc.), in transportation unit	Frequent updates for new location and movement	Not only where it is, but what is close to it, who moved it, its path to get there, and its predicted path forward; location positions that are time stamped from mobile devices

Source: (Waller and Fawcett 2013).

While analytics do provide value in solving business problems, it only does so for a limited time, as the company and the environments of which it is a part evolves. Thus, analytics solutions need to be maintained over time by either realigning the analytical model or changing the data, or ultimately discontinuing the analytical model (Liberatore and Luo 2010; Lavalle et al. 2011; Larson and Chang 2016)

The exploratory process of constructing an analytical artifact is experimental and is based on well-designed experiments, and by iteratively improving the artifact based on intermediary steps where the constructed artifact is evaluated by solution developers and users (Bose 2009; Viaene and Van Den Bunder 2011; Marchand and Peppard 2013; Larson and Chang 2016; Carillo 2017; Herden 2019). The artifact is often constructed as a pilot or PoC. Even though the construction of an analytical artifact is exploratory in nature and thus the design of the final solution is unknown, the process of constructing an analytical artifact can be structured (Herden 2019). One of the most popular process frameworks for structuring the analytics process is the CRISP-DM framework (Herden 2019; Kridel and Dolk 2013; Subramaniyan et al. 2018; Shearer 2000). The CRISP-DM framework proposes six steps for managing the construction and deployment of an analytical artifacts. The framework starts by gaining a business understanding and iteratively identifying a business issue by comparing business issues with the available data. Once a business case has been identified, the data is prepared into formats that can be used for the following modelling step. In the modelling step, analytical models are iteratively constructed and evaluated until they successfully address the business issue. The final step is to deploy the model into the business processes. The CRISP-DM framework has also been used to construct the analytical artifacts in this thesis with satisfactory results.

It was found in article 3 that by the use of the CRISP-DM framework, artifacts could be constructed and deployed quickly. However, this relied on the prerequisites that the data was easily available in the right formats, that the right IT resources were available, e.g. in the form of having access to cloud computing, and that the right analytical and IT capabilities were available, as well as having access to domain knowledge.

Consequently, two barriers for maturing the use of analytics were identified. The first barrier is a data barrier, where data needs to be traceable and aggregated to the desired level of analysis. Passing the data barrier enables diagnostic, predictive and prescriptive analytics to be constructed and deployed. In other words, by passing the data barrier, cross-functional reports and advanced analytical models can be constructed and deployed to address a business issue. The second barrier identified is a capability barrier. The capability barrier refers to the need for human capabilities, which is a prerequisite for doing predictive and prescriptive analytics. Human capabilities refer to the technical capabilities of IT, data management, and analytics. It should also be noted that having access to domain knowledge is identified as crucial for the construction of an analytics solution that solves a real business issue (Herden 2019; Davenport and Harris 2007). The required capabilities depend on the business issue that is addressed, which depends on how advanced the analytical model is, how easily available data are, and what tools are provided for the solution creators. Additionally, different capabilities are required for different construction phases. The first construction phase, where the goal is to gain an understanding of the feasibility of solving a business issue with the available data and analytical models, domain and analytical knowledge are required. Once a business case has been scoped, the next phase is to prepare the data and create an analytical model. This phase requires data management, IT and analytical capabilities. Once a model has successfully been constructed, the model needs to be deployed, which can be seen solely as an IT task. Thus, only IT capabilities are needed for the final deployment phase, where the deployment phase would ideally be automised with no need for human interaction.

While a single worker, e.g. a data scientist, can possess these capabilities, it is recommended to rely on cross-functional teams instead (Herden 2019; Larson and Chang 2016; Marchand and Peppard 2013; Seddon, Calvert, and Yang 2010). The primary reason is that such a data scientist is hard to find, costly to hire, and can potentially be a bottleneck for the company (Herden 2019). Instead, teams should be comprised of a mix of technical and business knowledge contributing to generating insights and fostering learning between team members (Larson and Chang 2016; Marchand and Peppard 2013; Seddon, Calvert, and Yang 2010). The technical members ensure that the analytical solution is constructed correctly and that it is deployed following the deployment steps of the company (Liberatore and Luo 2010; Larson and Chang 2016). Cognitive experts ensure that the analytical solution addresses the business process to ensure that it enables better decision-making and that the insights are properly delivered to its intended consumers (Marchand and Peppard 2013; McAfee and Brynjolfsson 2012; Wixom, Yen, and Relich 2013; Larson and Chang 2016).

5.1.1. Analytics decoupling point

Following the processes of constructing and deploying an analytical artifact as described entails that most of the work within analytics is exploratory and only the deployment can be treated as a pure exploitive process. Ideally, exploration and exploitation should be dealt with by different people with different cultures and competencies, and as such, the two processes should be decoupled from each other. The resulting decoupling point between the explorative and exploitive processes can be depicted as Figure 10, which is based on the CRISP-DM framework.

Figure 10. Unique business issue analytics decoupling point based on CRISP-DM.

The management of the analytics projects is governed by two different working groups for the exploratory and exploitive groups. The exploratory group will have a dialogue with the business, which has domain knowledge and consists of workers with analytical and data management capabilities. The exploitive group will have none of these capabilities, but instead have IT capabilities for deploying the solution into a company's IT system landscape. In this way, the unique business issues of the individual company can be addressed by the use of custom analytic solutions.

In article 3, an analytic artifact was constructed based on the use of the CRISP-DM framework, where a business issue was identified to predict a production value, in this case a 24-hour pH value, based on the previous production processes in the production of blue cheeses. The analytic artifact was constructed using explorative approaches, where the final analytical artifact could predict the 24-hour pH value, prescribe actions for reaching a desired pH value, and explain how the analytical model makes its decisions. However, a similar business issue was identified at another dairy, producing mozzarella cheeses, who also wanted to predict a production value. In this case, it was a different kind of pH value, where there was a desire to test the applicability of the constructed analytical artifact in the mozzarella dairy. The data of the mozzarella dairy was prepared following the guidelines from the analytical artifact constructed for the blue cheese dairy, and the analytical model was simply retrained on the prepared production data of the mozzarella dairy. The results were that the model delivered accurate results and the analytical artifact could be used and deployed without much exploratory work needed. The findings indicate that it is possible to move the decoupling point, as depicted in *Figure 11*, given that specific prerequisites are met.

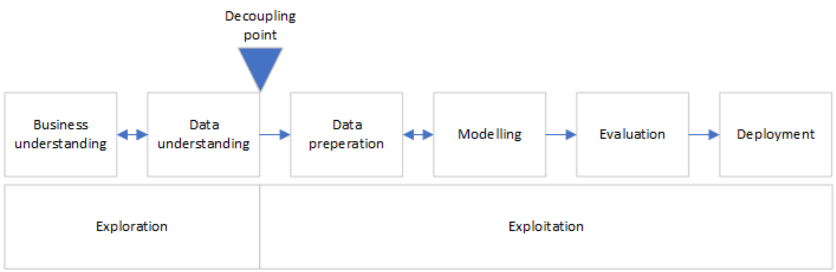

Figure 11. Common business issue analytics decoupling point based on CRISP-DM.

These prerequisites are that the analytical artifact follows the analytical paradigm of being constructed based on data instead of being purpose build. Additionally, the data needed to be traceable and aggregated to the level of the unit of analysis. Finally, the business issue addressed by the initial construction of the analytical artifact must match with other business issues. In the above-mentioned case, both business issues were to predict a production value given data from previous production processes. Essentially, such an analytical artifact would be useable for any cheese dairy that wishes to predict a production value, which could be predicting the final quality of a cheese.

The consequence of this is that if common business issues can be identified for a business, an analytical artifact can be constructed and maintained centrally and deployed to relevant entities, which enables analytical artifact to be scaled at low cost. Essentially, the use of the analytical artifacts becomes primarily an IT task, where data pipelines need to be set up and the artifacts need to be deployed, and the exploratory part is to identify if a business issue matches with an existing analytical artifact. Subsequently, the scalability of an analytic artifact depends on the identification of similar business issues across a company. By applying this approach, it can be possible to address the causality dilemma of needing a good data infrastructure to identify business use cases, where to have good data infrastructure requires that there are good enough business cases (Herden 2019). If a business issue is unique, it must be treated as such, where the exploratory and exploitive processes are divided, as depicted in *Figure 10*.

5.2. O&SCM IT value mechanisms

The exploratory value process is mainly driven by the use of analytics, whereas the exploitive value process is driven by the use of IT. The previous section described and discussed the value related to analytics, and this section describes the value mechanisms of O&SCM IT. The section first presents how IT creates value and how IT relates to the use of analytics for O&SCM companies. Next is business IT value defined, which is related to the analytics value definitions of Brinch (2018). The outcome of this section will be used together with the value mechanisms of analytics to construct a value framework.

It is generally accepted that IT does not create value by itself, but does so in combination with complementary resources, such as by humans and processes (Bayer, Haug, and Hvam 2020; Neumeier et al. 2017). As such, the use of IT must fit with the organisational structure of the individual company, and the effects of using IT must initiate organisational change (Neumeier et al. 2017). Thus, most IT value research has focused on the contextual factors that influence the effectiveness of IT (Bayer, Haug, and Hvam 2020). Examples of contextual factors for O&SCM companies are business process engineering (Altinkemer, Ozcelik, and Ozdemir 2011) and IT management (Khayer, Bao, and Nguyen 2020). Thus, to research value within IT means to research the contextual factors, to explain the different effects of different companies (Wiengarten et al. 2013). Consequently, it can be difficult to research value within IT, as the value outcome consists of multiple variables, where IT is only one (Bayer, Haug, and Hvam 2020).

However, to evaluate the value of IT within the scope of analytics, EIS and O&SCM, the contextual factors can be narrowed down to a few select ones. The concept of CSF in relation to implementation and assimilation has been extensively researched within the field of EIS, where some main CSF are top-management support, user skill/training, performance evaluation, context-dependent configuration (country, industry, implementation life cycle, culture and maturity [technology, people, systems]), implementing the project as a business project, and having a large budget (Asmussen and Møller 2020). A main challenge with the use of analytics and EIS is dealing with both system and data heterogeneity, which stems from different IT systems with different data models (Mansour, Millet, and Botta-Genoulaz 2018; Saberi, Hussain, and Chang 2017; Cupek et al. 2018; Asmussen and Møller 2020). Further, this is becoming an even greater issue with the introduction of real-time and unstructured data (Saberi, Hussain, and Chang 2017; Asmussen and Møller 2020). Several authors have addressed this issue by proposing conceptual frameworks (Weihrauch, Schindler, and Sihn 2018; Cottyn et al. 2011; Jeon et al. 2017; Cupek et al. 2018; Mansour, Millet, and Botta-Genoulaz 2018; Jiang et al. 2007). Some standards for structuring data have been proposed, such as the ISA-95 standard for manufacturing, but it is uncertain how to use that for analytics (Asmussen and Møller 2020; Cottyn et al. 2011; Cupek et al. 2018; Mansour, Millet, and Botta-Genoulaz 2018).

The use and integration of analytics is distinctive from EIS implementations, where analytics can make use of any type of data, utilising open-source software and human capabilities (Asmussen and Møller 2020). The use and integration of analytics is often managed as smaller projects and can be constructed quickly by a few people without interrupting daily operations and can also be deployed quickly through microservices, where the enterprise data of the EIS can be read via APIs. On the other hand, EIS projects are often large, costly, and have a big impact on the day-to-day of the company (Asmussen and Møller 2020). Current EIS offerings are often tailored towards reporting, control and execution, but they lack predictive and prescriptive analytical models (Asmussen and Møller 2020). Thus, the role of EIS is to manage business processes, where analytical artifacts can be used to construct advanced analytical models. Essentially, the insights and actions derived by analytics can be integrated with the BPM of a company that is managed in the EIS. However, this integration must be led by the successful use of IT.

Bayer et al. (2020) investigated how IT business value can be created and create competitiveness for a company and present a framework that addresses that issue. They borrow the concepts of O&SCM competitiveness from Porter (1985), which are defined as efficiency, quality, innovation and customer responsiveness. These dimensions of competitiveness are compared with three inherent IT capabilities: transaction, exchange, and codifying capabilities, defined as:

- Transactional capability: “The ability to automate existing business processes and process, interpret and synthesize information” (Bayer, Haug, and Hvam 2020).
- Exchange capability: “The ability to exchange information within and across firms, enabling fragmented entities to connect, communicate and collaborate seamlessly” (Bayer, Haug, and Hvam 2020).
- Codifying capability: “The ability to capture and integrate information by making it easy to collect, organize, store and access across the organization” (Bayer, Haug, and Hvam 2020).

The presented framework is depicted in *Table 10*, where IT capabilities are compared to the dimensions of competitiveness.

Table 10. Inherent IT Capabilities for Business Competitiveness.

Dimensions of competitiveness	*Transactional capability*	*Exchange capability*	*Codifying capability*
Efficiency	- Increased ability to process and analyse information for decision-making - Increased ability to automate processes for increased output	- Increased ability to communicate and collaborate to achieve information synergies	- Increased ability to access information quickly
Quality	- Increased ability to process information (error processing) to achieve better product or service quality - Increased ability to automate alerts (error identification)	- Increased ability to communicate and collaborate to achieve higher product or service quality	- Increased ability to access information in a consistent manner to achieve better decision-making
Innovation	- Increased ability to process information to identify competitive strength or innovations - Increased ability to process information to visualize the design	- Increased ability to communicate and collaborate to achieve information synergies	- Increased ability to access organizational memory to achieve innovation
Customer responsiveness	- Increased ability to process information (strategic processing) to meet customer needs	- Increased ability to coordinate and manage remote processes to achieve quicker responsiveness	- Increased ability to access market requirements to achieve increased responsiveness

Source: Bayer, Haug, and Hvam (2020).

The framework proposes that to become more efficient, data needs to be available quickly for processing into actions or insights for decision-making, and the outcomes need to be easy to communicate to relevant stakeholders. Further, for exploitive processes, the processing of data into insights and actions needs to be automated. Much of the same capabilities are needed for improved quality; however, better quality is achieved by ensuring consistency in data collection, management and processing, which ideally leads to products or services of higher quality. The competitive aspect of quality can in most parts be directly related to exploitation. To increase innovation, explorative processes need to be enforced. The explorative processes are enforced by enabling the sharing of internal and external knowledge and data, where there is room to experiment to quickly identify competitive strengths and innovation by the processing of (new) data and organisational knowledge. Last, customer responsiveness is achieved by incorporating external data from the market and processing that data to identify and meet customer demands.

To summarise, to gain value from business IT, a company needs to be able to automate and process the data of the company and, from the external environment, enable the ability to easily share, collect, store and organise data in the company. These findings can be used to support the generation of explorative and exploitive analytical value by ensuring the applicability of value discovery, analytics and value creation from an IT perspective. To show how the different IT capabilities relate to the generation of analytic value, *Table 11* has been created.

Table 11. Comparing IT Capabilities with Analytics Value Definition.

Dimensions of competitiveness	*Transactional capability*	*Exchange capability*	*Codifying capability*
Efficiency	Analytic & value creation	Value discovery	Value discovery & value creation
Quality	Analytic & value creation	Value creation	Value discovery & value creation
Innovation	Analytic	Value creation	Value discovery & value creation
Customer responsiveness	Analytic & value creation	Value discovery, analytics, & value creation	Value discovery & value creation

The table shows that the generation of analytic value is involved with all three IT capabilities. In other words, to create analytical value, all three IT capabilities are needed.

The following section presents the value framework of integrating analytics and EIS for the O&SCM company, which is based on the findings of this chapter, as well as chapter Chapter 3.

5.3. Value framework

So far, different aspects of generating value have been presented and discussed. The purpose of this section is to bind all of these findings together into an analytic value framework. The framework is constructed based on the analytic value definitions by Brinch (2018) and the CRISP-DM analytic process model. The supporting activities are also presented, such as how IT supports each analytic value stage, in addition to the relevant CSF and value mechanisms. The remainder of this section describes and discusses the value framework, which is depicted in *Figure 12*.

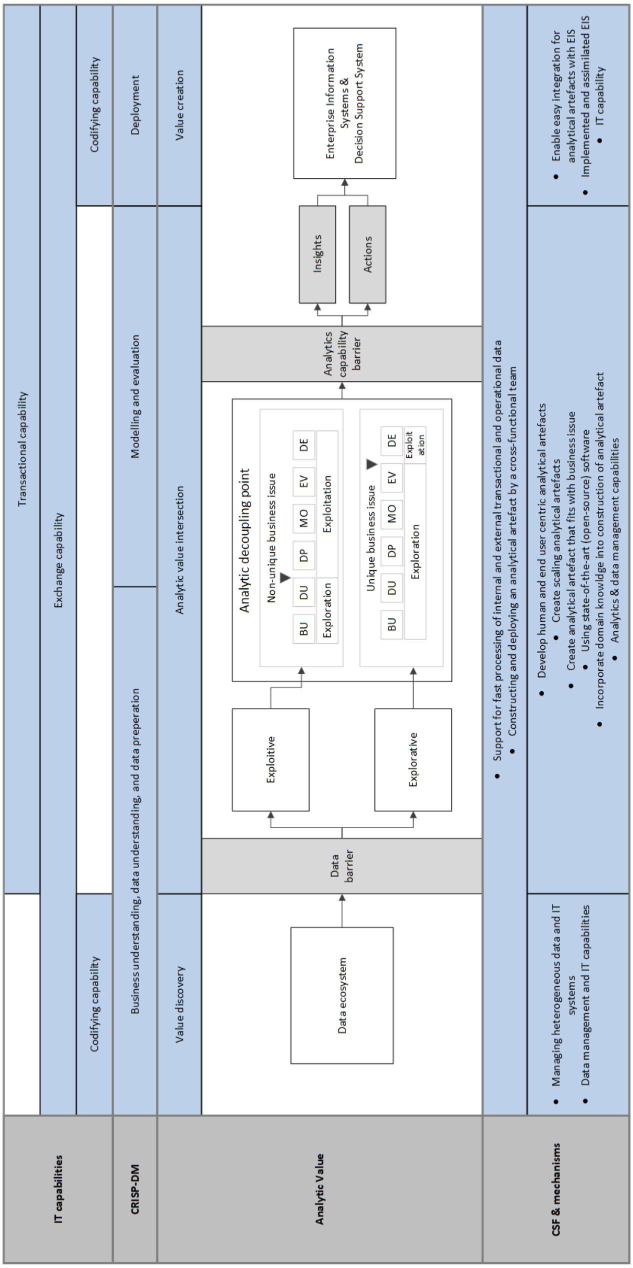

Figure 12. Analytic value framework.

The framework is divided into three analytical value parts: value discovery, analytic value intersection, and value creation. Each part of the framework is unique in generating value and how IT and CSF can be used to support the creation of value. However, it should be noted that the general creation of value is dependent on successfully managing all value stages. Consequently, the framework will now be described by presenting each analytic value part sequentially, starting from value discovery and ending with the value creation value part. The section is concluded by a discussion of the framework in its entirety.

Value discovery is about the management of data from different IT systems and data sources, which acts as the data foundation for constructing analytical artifacts. Subsequently, value discovery supports the business understanding, data understanding, and data preparation analytical processes. A successful management of data discovery entails that internal and external heterogeneous data types and IT systems are dealt with so as to provide data that can easily be shared, collected, stored and organised. To achieve this, the IT capabilities of codifying and exchange capabilities should be utilised. Besides the requirements from an IT system perspective, human capabilities are also essential in that data needs to be gathered and processed into a format that can be used to create an analytical model that solves a particular business issue. Thus, for value discovery, the IT and data management capabilities are essential.

Value discovery is essential in the creation of analytical artifacts, where the successful application of the processes within value discovery is needed to pass the data barrier. There is not just one way to pass the data barrier, which depends on the data needs of the analytical artifact constructed in the analytic intersection. However, a general rule of thumb is that data needs to be traceable if the analytical artifact uses data from different O&SCM functions, and that it needs to be aggregated to a desired level, such as to the level of analysis of the analytical artifact.

The analytical value intersection is the bread and butter of processing and transforming data into analytical artifacts that can be used to create either insights or actions for improved performance for a company. The process of constructing an analytical model is divided into explorative and exploitive processes. The process of exploration is used to construct new models for a new business issue, where the exploitation process is used to automate and deploy an analytical artifact into a business process, either as a stand-alone solution or by integrating the analytical artifact into a data pipeline of either a decision support system or EIS. The degree of exploration and exploitation depends on whether a new business issue is being addressed or if previously constructed artifacts can be reused. If a new or unique business issue is being addressed, all the CRISP-DM processes are exploratory, except for the deployment process, which can be seen strictly as an exploitive IT process. On the other hand, if an analytical artifact based on the learning of data has previously been constructed to address a similar business issue, the analytical artifact can simply be retrained on new data, effectively treating all processes except identifying the business issue as exploitive. Consequently, in the latter case, it will be possible to automate the entire process from preparing the data to fit with the data model of the analytical artifact, retrain the analytical artifact including hyperparameter optimisation, and automatically deploy the model to its intended target. Thus, it will be possible to scale the training and deployment of analytical artifacts, given that similar business issues can be identified across a company.

The IT capabilities for enforcing the analytic value intersection are transactional and exchange capabilities, where IT systems should support the ability to process the data as desired, which in most cases entails the use of open-source software and the ability to share both the data and outcomes of the analytical models in the form of insights and actions with the relevant outlets and stakeholders. The CSF for the analytic value intersection is to first ensure that the analytical artifact solves a real business issue and that it is human- and end user-centric. To enable the creation of such an artifact, domain knowledge should be incorporated into the construction process of the analytical artifact. The construction of the artifact should be based on the use of state-of-the-art software, which in most instances would be the use of open-source programming language such as R, Python or Julia. If it is possible, companies should aim to create analytical artifacts that can be scaled across the company. Last, analytics and data management capabilities are seen as essential for the management and creation of an analytical artifact that complies with the prerequisites of creating value within the analytic value intersection. As a consequence, to be able to move from processing the data to insights and actions, the analytical capability barrier needs to be passed. It is therefore essential to have workers with the right competencies to create analytical artifacts that create relevant and useful insights and actions.

The last analytical value step is value creation, where the insights and actions created can be consumed by relevant end users and are either delivered as a standalone system or report or integrated into a data pipeline of a decision support system or EIS. Consequently, the systems that the artifact is going to be integrated with must be successfully implemented and assimilated. Additionally, it should be easy to integrate an analytical artifact with either a decision support system or EIS, as speed of integration is important. This can often be done via the use of APIs and deployment of containers. Further, as this stage is mostly related to deployment and integration, most of the activities can be related to IT activities, which means that workers in the value creation stage should possess sufficient IT capabilities. For a successful value creation step, all the IT capabilities of transactional, exchange and codifying capabilities are needed. For value creation, the processing and integration of insights and actions must be easily, and optimally, automatically integrated into the company’s business processes. The insights and actions must be able to be shared across the company to any relevant stakeholder, and be managed and stored to be used where it may be applicable.

The value framework presented ties together the understanding of value for analytics, (big) data, and business IT, with mechanisms of creating that value. The value framework shows that all of the value stages are interconnected and thus cannot work independently. Value for a company is only created once an action has been made as a consequence of applying an analytical artifact, which entails that any undeployed artifact cannot create value. It therefore becomes essential to minimise the cost of all processes before the deployment stage in an exploitive manor. It therefore stands to reason that creating an analytical artifact that can address a business issue that is faced many times in a company would be the most value-creating path to keep the cost of exploration as low as possible. However, this is of course only true if we do not consider the concept of value capture, where solving a business issue brings most value if it is aligned with the strategic goals of the company. Additionally, while exploitation does minimise cost, it does not explore new opportunities, and as a consequence, potential new application of analytical artifacts can be missed. Therefore, companies should seek an ambidextrous management of creating and managing analytical artifacts, where the use of exploration and exploitation is balanced. While it can be difficult to define how to balance exploration and exploration, a rule of thumb is that more focus should be used on exploration in unstable environments and more focus should be on exploitation in stable environments.

The framework aids with an understanding of specifically *how* value is created, which can both be used by academics and practitioners. The value framework is seen as an addition to the knowledge base, where understanding of value mechanisms has been missing. While the value framework does present value for practitioners, it has mainly been constructed to be applicable for an academic audience. Thus, to operationalise the value framework, an approach will be presented in the following section for how to employ the framework practically, using current technologies and methods available. The section will make use of the value framework by creating instantiations for exploratory, exploitive and ambidextrous organisations, which are easily operationalisable. Further, two demonstrators are presented to show how to practically use the value framework and to evaluate the use of the framework in a real environment.

Chapter 6. Integrating analytics with EIS approach

This section presents an operationally focused approach to the value framework presented in this thesis. The section combines the identified findings and mechanisms for the creation of value in the analytics, EIS and O&SCM intersections into an approach that addresses the issues of integrating analytics with EIS from an IT perspective. The reason for creating an approach with an operational focus is that the identified mechanisms are presented one by one in the value framework, but the reality for most companies is that value is not created by addressing one of the mechanisms, but by addressing several mechanisms. Consequently, there is a need to communicate how multiple mechanisms can be addressed in one approach. Thus, the approach and value framework also need to be evaluated in a real environment, which is why two demonstrators are presented. The approach serves to both make the value framework more operational and is used to evaluate the value framework in a real environment.

The section is structured by first summarising and presenting the identified requirements for supporting the generation of value based on the value framework. Next are two concepts introduced that are used in the approach: the pace-layered application strategy and loosely coupled systems. This is used to construct an approach to deal with the issues of integrating analytics and EIS from an IT perspective. After having presented the approach, it will be instantiated into an exploratory, exploitive and ambidextrous framework, which visualises what an operationalisation of the approach can look like. However, it should be noted that the frameworks must not be viewed as the optimal use of the approach, but simply as instantiations that follow the requirements and enable the use of and integration with the exploratory and exploitive analytical processes with EIS. Finally, the section is concluded by presenting two demonstrators of the approach, which is conducted in the environment of Arla Foods. The two demonstrators show how analytics can be used and integrated in a demand planning and manufacturing case.

6.1. Identifying the requirements for constructing an approach

The identification of requirements for the proposed approach is based on the value framework, where the needed mechanisms for value generation are identified. First, a general description of the needed requirements is presented, which is followed by specific requirements for the explorative and exploitive analytical process flow.

The use of analytics is based on the access to software that can process and have access to relevant data. Further, to generate value, analytics must be used on a business-relevant problem and deployed to be easily consumed by relevant end users. While this may sound intuitive, it can be difficult to accomplish. Having access to software that can construct or make use of advanced analytical models is uncommon in companies today, where most often the use of analytics is done in either EIS or BI systems, which do not enable the use of advanced analytical methods (Ivert 2012). Consequently, for constructing an advanced analytical model, other IT systems or software need to be used. Obtaining relevant data means recording, storing and managing data that is not only recorded by the EIS, but also by other instances such as IoT devices or spreadsheets. Thus, there is a need for companies to manage the use of both heterogeneous data and heterogeneous IT systems. Additionally, both the data and processing of data should be enabled to easily and quickly have access to any relevant data and to deploy the constructed analytical artifacts into the business processes of a company. The analytical process should be structured by the use of CRISP-DM, and the company should actively try to balance explorative and exploitive analytical processes. The analytical process should be supported by a cross-functional team consisting of members with technical, data management, analytical IT capabilities and access to domain knowledge. For a successful integration of an analytical artifact into an EIS, it is key that the EIS has been implemented and assimilated into the company. Finally, the creation of value is obtained once relevant data has been processed to generate insights or actions that makes a positive change in the company, which in most instances would be by either providing a report or integrating the insights or actions into a business process. The management of constructing and deploying analytical artifacts is essential in creating value for a company, which is now further elaborated on.

Central to the construction of the analytical artifact is to have access to relevant data and return the results so they can be consumed in a business process workflow. The exploratory workflow of analytics often consists of getting data from different data sources and constructing a model iteratively either until the business is satisfied with the solution or the pilot ends. Thus, there is a need for a lot of flexibility where the workers who construct the artifact will need access both to enterprise data and relevant external data. In the exploratory phase, it is not necessary to have access to a data pipeline, where having access to data files such as CSV or parquet can be sufficient. On the other hand, the exploitation of analytics is distinctive where the constructed analytical artifacts must be integrated into a data pipeline and business workflow in an automated fashion. The data pipeline for the exploratory workflow will mainly be using OLAP, where data is stored in a database, e.g. in a data warehouse or data lake. In this way, data can be stored, cleaned and aggregated and be used to train models, which may take hours or days. On the other hand, once the analytical artifacts are constructed, they must be included in an OLTP data pipeline; if reliable, real-time execution is essential.

An important differentiation between the processing of analytical artifacts is whether the data is streamed or processed in batches. In reality, there is not much difference between the two, where batch processing has a clearly defined start and end date and stream processing never ends. Many of the analytical software packages can manage both stream and batch processing, where Spark, for example, performs stream processing using a micro batch processing approach, and Apache Flink processes batches on top of a streaming process (Kleppmann 2017). Even though the concepts are technically similar, there are important differences in how they are applied. Batch processing can be seen as off-line processing, where a large amount of data can be processed, possibly for a long time, to produce an output, e.g. in the form of an analytical model. Stream processing, sometimes also referred to as near-real-time processing, processes a much smaller amount of data, but consequently can process the data into an output much faster. The definition of near-real-time is quite vague and can vary depending on the applications where near-real-time can fluctuate between seconds to tens of minutes. As a note, it is often unclear what reports from the industry or journal papers mean by the term “real-time-data”, where it would often be better classified as near-real-time data. However, for true real-time analytics, analytical services can be used, where an analytical service waits for a request from a client and responds as quickly as possible. The output of the data processing can either be in the form of an input for human consumption or another data stream. Humans consume the output by getting emails, reports or notifications or by streaming the output to a real-time dashboard (Kleppmann 2017). The output for other data streams can be used as an input for other applications, where an example is to include the output of a market analysis into a sales forecast or a newly calculated lead-time to update the transportation lead-time. The difference between the two types of data processing can be exemplified by the construction of a machine learning model. Constructing a machine learning model requires that data is stored and aggregated as a batch where the training time can vary from minutes to days. However, once the model is finished being constructed, the machine learning model can then be integrated into a streaming data pipeline and business workflow, where the machine learning model can take much smaller inputs and thus return an output with very little latency. Thus, both stream and batch processing are important for the construction and deployment of the analytical artifact, but serve different purposes.

The data used for constructing the analytical artifacts can be categorised into structured or unstructured data. Structured data is also called relational data and is data that fits into a relational database or spreadsheet. The data is structured in a key-value structure, where the key can be called to return the attached value. Unstructured data, or non-relational data, do not have this key value relationship. Examples of unstructured data are video, audio or text such as tweets. Processing structured data is straightforward and can in most cases be easily applied in machine learning models, if the data quality is good enough. Unstructured data, on the other hand, is more difficult to process, as data mining or machine learning techniques must be used to structure the data into a structured, useable format. As unstructured data cannot be saved into a relational database, other alternative solutions for storage are provided. A popular choice in the industry is to make use of NoSQL databases or data lakes, where the raw, unstructured data can be stored. It is important that the approach presented in this thesis will be able to consider both structured and unstructured data to ensure that all relevant data are available.

6.1.1. Issues in integrating analytics with EIS

Having discussed the requirements for making use of analytics, the challenges of integrating the use of analytics with the current use of EIS must also be discussed.

There are significant differences between the use of analytics and EIS, such as the rate of change between EIS modules and analytic artifacts. EIS modules are large IT implementations, which change slowly once implemented, i.e. changes are made every three-to-five years (Gartner 2012b). On the other hand, analytic artifacts are deployed as small IT artifacts, usually in containers, which can constantly be updated to accommodate new developments in either technology or demands of the business. However, even though the business process changes slowly, they do change over time. Consequently, analytical artifacts that once fit the process may no longer fit over time. This highlights an issue where analytic artifacts must be able to integrate into the business processes quickly once changes have been made to the EIS business process. Additionally, as the general use of analytics in companies is immature, managers of the companies do not know how to make the best use of these analytical artifacts. Essentially, analytics should be able to integrate with EIS as PoC or as a pilot to investigate whether an analytical artifact brings value to the company. Once the pilot is accepted by the business, the analytics artifact should be integrated as a part of the business workflow as an IT integration project. The integration of the analytical artifacts should ideally be non-intrusive for the business workflow, as analytical artifacts could potentially be integrated weekly. Thus, there is a need to support both an explorative process of identifying where analytical artifacts can create value, construct and deploy them as an exploitative process, where an analytical artifact is integrated, ideally automatically, with a business workflow.

Further, the use of advanced analytical models requires that there is access to internal and external data. Importing external data into EIS can be cumbersome and costly. External data is, in most cases, easy to integrate into the analytics workflow, where data can be gathered from databases or locally stored data files. However, the analytical artifacts cannot solely rely on external data and will in most instances also need the enterprise data of EIS. An important issue to solve is therefore to ensure that analytical artifact, will have timely access to both internal and external data.

Additionally, the solution to these issues must consider the mechanisms and CSF identified in the value framework. That is, the integration of external and internal data must enable the possibility to overcome the data barrier and manage heterogonous data from heterogeneous IT systems. Analytical artifacts should be constructed to address a relevant business issue and be human centred. It should be possible to scale an analytical artifact, i.e. deploy an analytical artifact across different IT systems. The analytical artifacts should be based upon open-source software, where qualified and capable workers will be able to construct business-fitting analytical solutions.

6.2. Concepts for overcoming integration issues

In this section, two concepts will be introduced to address the identified issues of integrating analytics with EIS. The section will first present the concept of pace-layered applications to address the issue of different paces between EIS and analytics. Next follows a presentation of loosely coupled systems, which highlights how IT systems and artifacts can be integrated without interrupting the daily business workflow.

6.2.1. Pace-layered application strategy

One of the main challenges in integrating analytics with EIS is that they operate at different levels of pace. A solution therefore needs to be found, where the stable and predictable management of the business processes can continue to operate, as they do today, and at the same time enable the integrating of analytical artifacts into or supporting a business process. Dealing with a similar issue, the research and advisory company Gartner proposes a pace-layered application strategy (Gartner 2012b). The strategy proposes that IT systems should be separated into three layers based on their rate of change. The three application pace layers are:

- System or records
- System of differentiation
- System of innovation

The system of records layer consists mainly of standard issue software, which supports core business transactions and manages critical master data such as financial and sales records. IT application in this layer has typically not been modified to fit into the company context, and as such can be implemented in most companies. The timespan of change ranges between ten and twenty years.

The system of differentiation layer consists of IT applications that differentiate companies within the same industry from each other. Thus, the IT applications within this layer are often customised to fit the focal company’s business processes.

For example, two companies within the same industry would likely not process sales inquiries in the same way, which means that the IT applications need to support the unique business workflow of the company. The timespan of changes in this layer ranges between three and five years.

The final application layer is the system of innovation layer. In this layer, new ideas and technologies are tested, often as either pilots or PoC. The timespan of applications in this layer is between 3 and 12 months.

Gartner made an overview of the characteristics of each layer, which is depicted in *Table 12*.

Table 12. Characteristics of the Pace-Layered Application.

CHARACTERISTIC	RECORD	DIFFERENTIATION	INNOVATION
Process Characteristics	Well understood	Well understood	Unique
	Slow to change	Unique	Not well understood
	Highly integrated	Highly configurable	Dynamic
		Autonomous	Ad hoc
Data/Information	Highly structured	Internal and external	Structured and unstructured data
	Well managed	Some unstructured	Heavy reliance on external data
	Mainly internal	More dynamic	
	Audited		
Content	Static/stable	Both	Dynamic
Analytics	Reporting	Planning	Predictive
	Historical	Budgeting	Scenario-based
Security	Tightly controlled	Distributed control	Federated control
	Managed complexity	Manageable complexity	High potential complexity
Collaboration	Limited	Moderate	High

Source: Gartner (2015).

The table shows that predictive and prescriptive (scenario-based) analytics should be placed in the innovation layer, and planning and budgeting should be placed in the layer of differentiation. While it is true that predictive and prescriptive models would initially better fit into the innovation layer, some of these models would end up in the layer of differentiation. Predictive and prescriptive models would in some instances have short life spans in environments that change rapidly; however, in other environments with less rapid changes, some of these models would have a longer lifespan and thus need to be integrated into the layer of differentiation. In the context of a pace-layered strategy, analytical artifacts would be constructed as pilots or PoC in the innovation layer, and as the artifacts are evaluated, they are either going to be discontinued, replaced or moved from the innovation layer to the differentiation layer. It should be noted that while the analytical artifacts start as a pilot or PoC, when finally deployed they will be able to be deployed as a pilot or remodelled into a full application.

In summary, by making use of the pace-layered application strategy, it will remain possible to continue to rely on the BPM of the EIS, but enhance the business processes by constructing analytic artifacts in the innovation layer, which either remains in that layer or is constructed into full applications in the layer of innovation or differentiation.

6.2.2. Loosely coupled systems

A main concept in the pace-layered application strategy is that IT applications are loosely coupled. Loosely coupled systems have two main benefits (Kleppmann 2017). One, is that systems can run asynchronous event streams, which means that when one application fails, other applications continue to work unaffected. Additionally, if the integration between applications is based on log-based integration, once the error is fixed, the application can catch up without any loss of data. The second main reason for applying a loosely coupled system is that applications can be constructed, improved and maintained independently from each other (Kleppmann 2017). This enables scalability within a company and allows companies to hire teams that can work on different services, which enables workers to become specialised and reduces coordination efforts.

It is assumed that in a loosely coupled system, there is a separation between the stateless application logic and state management (Kleppmann 2017). In other words, applications that manage the business workflow should save their data into a database and not store the data in the application. The same holds from the inverse perspective, that databases should never have application logic built into it. Central to this way of thinking is therefore to have many applications that manage the business workflow or artifacts which write and read from one or more databases. The most common way of handling this relationship is to make use of a client-server relationship. Essentially, a server is exposed to a network through an API, for which clients can request. Popular protocols for managing this interaction are representational state transfer (REST) and simple object access protocol (SOAP). The trend is therefore to break larger IT applications down into smaller services, such as those connected through REST APIs, which is also called the SOA approach.

Making use of the loosely coupled systems enables companies to integrate the analytical artifacts constructed outside of EIS and, consequently, simultaneously manage the value discovery and value generation from exploratory and exploitive analytics. Thus, analytical artifacts can be constructed on a laptop, workstation or virtual machine in an exploratory iterative fashion as part of the innovation application layer, where access to relevant data has been established. If the analytical artifact does successfully address a business issue, it can continue being deployed in the innovation layer if the expected life expectancy is less than 12 months, or else be deployed in the differentiation layer. In this way, analytical artifacts can have access to all relevant data, where the construction or deployment of the analytical artifact will not disturb other IT applications.

6.3. Presenting the approach

Having summarised the identified mechanisms and discussed the challenges of integrating analytics with EIS, this section presents an use of the value framework. The section first presents how the explorative and exploitive processes should be managed for the pace-layered strategy. Next, will the pace-layered strategy and the explorative and exploitive analytical processes be presented, which visualises how the value framework can conceptually be constructed. The approach of this section will be used as the foundation for instantiating the exploratory, exploitive and ambidextrous frameworks.

The approach revolves around the concept of pace-layered application, which sets the frame of how exploration or exploitation is to be used, as depicted in *Figure 13*.

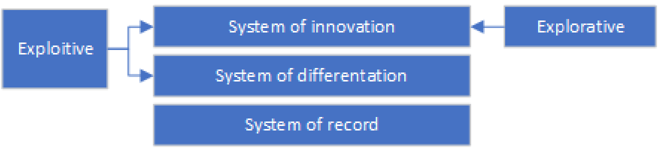

Figure 13. Exploration and exploitation in the pace-layered strategy.

The natural fit for the exploration of analytics is in the layer of innovation, which is characterised as dealing with ad hoc, dynamic problems, which rely heavily on the use of internal and external structured and unstructured data. The solution introduced in the innovation layer aims at solving unaddressed problems, which in most cases is the purpose of constructing an analytical artefact. As the introduced solution to the innovation layer consists of applications with a short lifespan, the construction and deployment of an artefact must be done quickly. For exploitation, which is mostly concerned with the deployment of an already constructed artefact, the deployment can be made in either the innovation or differentiation layer, dependent on the expected lifespan of the analytic artefact. Essentially, what is proposed is that there is a need for a great deal of flexibility in the layer of innovation, where constructed artifacts can be loosely integrated with the business process of the layer of differentiation. However, for the exploitive processes, the integration of analytical artifacts can be differently integrated, where artifacts with longer life spans can be more tightly integrated than artifacts with shorter lifespans. It could be argued that analytical artifacts, where the final solution is known and the expected lifespan is more than a year, should be constructed in the layer of differentiation. While this is true, this approach does not take that into account, as the general maturity of constructing analytical artifacts at most O&SCM companies is low, and the vast majority of artifacts constructed are expected to have either a short lifespan or an unknown final solution.

Figure 14 expands on the concept of pace-layered applications and represents the main approach of managing the exploration and exploitation of analytics for the pace-layered strategy.

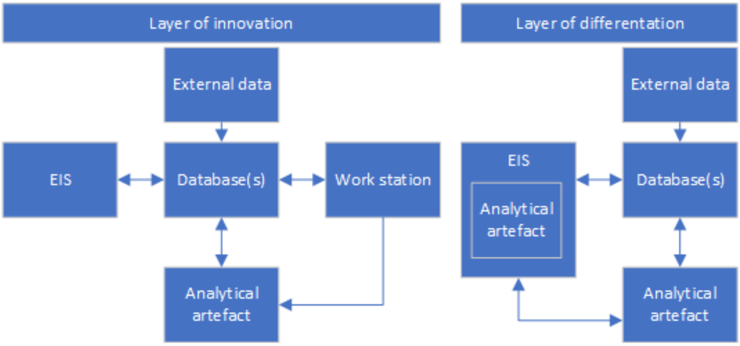

Figure 14. Approach integrating loosely coupled systems based on the pace-layered application strategy.

The approach is centred on the idea of loosely integrating IT systems, where application logic is stored in IT systems or artifacts and the output data is stored in databases. The layer of innovation is mainly concerned with exploration – which means it must provide easy, timely access to relevant data – where capable workers need to have the flexibility to process these data as they see fit. The data can come from many sources, including EIS, spreadsheets or external databases. In the proposed approach, all types of data are stored in one or more databases, which are connected to a work station. A workstation in this approach can be any form of computer, whether it is a regular computer workstation, laptop or virtual machine. The workstation will have the required software installed to both manage and process the data into analytical artifacts. Once the analytical artifact is ready for deployment, it will be deployed as a stand-alone application, as inspired by the microservice approach. In this way, the deployment of analytical artifacts can be done in a containerised environment, where data from a database can be sent to the artifact, which can process the data and return the processed data to the database. These processed data can then be read either by EIS or decision support systems or be read or presented in the form of reports.

The layer of differentiation is mainly concerned with exploitation, where it is assumed that an analytical artifact has been constructed and needs to be integrated as a part of a business workflow either as a full loosely coupled or less loosely coupled. The integration of an analytical artifact can either be deployed in the same manner as in the innovation layer, where the artifact receives and returns data to a database, where other applications can read the data. However, it is also possible to integrate the analytical artifacts more tightly with EIS, for example, if there are concerns regarding latency or reliability if the internet shuts down. The analytical artifacts in a manufacturing setting can be deployed as an edge device, where an analytical model is deployed on the local network of the manufacturing site, which can both process the data from the local MES system and send data to a centrally managed database.

While the presented approach is simple, it does address the mechanisms identified in the value framework. The approach manages heterogeneous data and IT systems by using a loosely coupled approach, where applications are managed independently and with a client/server relation. All types of data can be stored in central database(s), where data sources can be EIS, Excel spreadsheets, or external databases. The data can be processed in workstations that have both the required hardware and software for either processing data into the right formats or processing it into analytical models. In this way, workers with the right capabilities will have access to the right tools for their job and will have easy access to relevant data. The approach also enables the use of both explorative and exploitive processes, and does so without interrupting the daily operations of a company. Further, the approach enables the use and benefits of transactional, exchange and codifying IT capabilities. Essentially, data can automatically be processed and interpreted, and both the data and outputs of the data processing can be shared across a company for easy access, which supports the ability of workers of the company to collaborate. Finally, the approach enables the ability to capture, integrate and manage both information and data into company processes.

Having presented the approach for addressing the identified value mechanisms, the approach will be instantiated into an exploratory, exploitive and ambidextrous framework.

6.4. Instantiating the approach

This section presents three instantiations for how to integrate analytics with EIS based on the previously presented approach and the value framework. The instantiations are presented as frameworks, which relate to the exploratory, exploitive and ambidextrous analytical processes. The ambidextrous instantiation combines the exploratory and exploitive instantiations into one final framework. The ambidextrous framework will be evaluated by constructing and deploying analytical artifacts in two demonstrators. The instantiations can be done in many ways, where the presented instantiations are based on the author’s experiences from working at several companies as an SAP consultant, from an analytics start-up company, as well as from blogs and Arla Foods.

6.4.1. Exploratory instantiation

The purpose of the exploratory instantiation is to present a framework for enabling the explorative workflow when creating an analytical artifact, based on internal enterprise data and external data. The framework therefore visualises the entire flow from data collection, data storage, data use, modelling and deployment. The exploratory workflow is significantly different from the exploitive workflow, as there is a need to explore new models, data sources, or different applications to accommodate one or more business requests. As a consequence, many of the processes cannot be automised, where the exploratory framework is constructed to enable quick iterative construction and deployment of an analytic artifact. The framework is based on the previously presented approach, where data is stored centrally from the EIS and external sources, which can easily be read by a capable worker in a working station. Thus, the instantiation mainly addresses the innovation layer of the pace-layered strategy. The exploratory instantiation is presented in *Figure 15*.

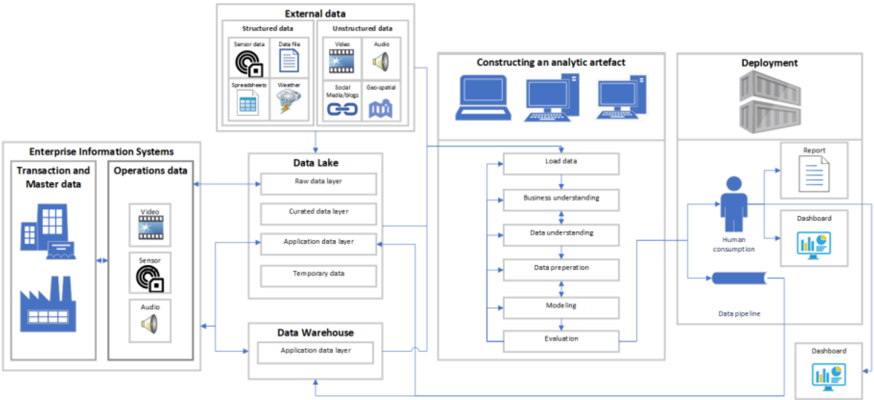

Figure 15. Exploratory framework for integrating analytics with EIS.

Central to the framework is that a worker, such as a data scientist, should have access to state-of-the-art software, such as the analytics open-source software languages and packages, as well as having timely access to relevant data. Thus, the framework proposes that the data scientist will be working on either a laptop, work station, or on a virtual machine, where all relevant software is available. The goal is to make all relevant data available outside of the EISs to ensure full flexibility and speed in constructing an analytical model, where the data can be extracted from central databases. Three different data sources have been identified for this instantiation. However, other data sources could potentially be added.

The first data source is a standard data warehouse, where the transactional and master data of the EISs are stored. The data in the business warehouse make use of schemas, which structure the data into specific formats and present the data as they are used in the EIS business workflow. It should be noted that the data in EIS are categorised into two groups. The first category is the transaction and master data, which cover transactional data, i.e. data that record an event with a time stamp and a value, and master data, which provides general data that rarely changes. Examples of master data are customer information, such as customer name and address, and transactional data would be data about the process of selling a product to the customer. The second category is operational data, which are data that are recorded and stored, not directly consumable in the business workflow for most EISs. Examples are sensors that record temperature, video capture of a production line, or audio recording of a machine for detecting machine breakdown.

The second data source is a data lake that can not only store the structured transactional data from the EISs, but also raw data and unstructured data. The data lake can store both relational data, such as sensor temperature readings, and non-relational data, such as video or audio recordings. The data stored in the data lake do not have schemas when written to the database, contrary to the data warehouse, and as such, the relationships between the data must be created when reading the data. This can be a complicated task that requires sufficient IT and data management capabilities, which in many cases makes extracting data from the data lake unavailable for the average business analyst. The proposed data lake is divided into four layers, which are:

- Raw data layer
- Curated data layer
- Application data layer
- Temporary data layer

The raw data layers consist of data that is stored in its original recorded form and consequently would need further processing to be useable for an application. The curated data layer consists of data, e.g. raw data, that have been cleaned, aggregated or joined with other data. Curated data can take many forms, which can be used in artifacts or data pipelines as SQL views. Curated data are updated as new data arrive; that is, a curated data set will continuously clean, aggregate and join data as new data arrive. The application data layer takes the curated data and transforms the data to be ready for consumption by other applications, such as EIS or analytical artifacts. The data in the application layer is transformed to be integrated with a specific business workflow and can be viewed as production-ready data. The last data layer is the temporary data layer. The temporary data layer is included in the exploratory workflow, as data sources which are not integrated into EIS or external data can be used in the construction of a PoC analytical artifact. The temporary data layer is important to include, as data that is recorded in other databases or Excel spreadsheets can be included in a PoC. By including the temporary data in the construction of an analytical artifact, the company will get a sense of the value of the data. If the data is found valuable, the company can take measures to store the data either in a business warehouse or data lake. Temporary data can be both structured and unstructured.

The last data source is the external data. External data is either stored in the data lake or sent directly to the laptop, work station, or virtual computer used for constructing the analytical artifact. Most of the time, it would be preferable to have the data stored in the data lake, as to have the data available for all workers, but in some instances, it can simply be easier and faster to store the data directly on the work station of a data scientist. The external data will in most instances be stored as raw data, which will later be curated. It should be noted that it is possible to store all relevant structured and unstructured data in the data lake and not just the ones depicted.

The construction of the analytic artifact follows the CRISP-DM process model (Wirth 2000), which enables an iterative approach of loading new data, understanding the business issues and preparing the data, which will be used for modelling, and last evaluating the model against a business objective. The construction of an analytical artifact can be iterated by either loading new data or by processing the data differently by preparing the data in new ways or changing how the analytical model is used, for example. The data used in the construction of the analytical artifact will in most cases be loaded as a batch.

Once the analytical artifact has been evaluated and accepted, the artifact will be deployed in a container. Two main outlets will consume the output from the analytical artifact. The outcome will either be directed towards human consumption or as part of a data pipeline, where other IT applications or artifacts can process the output. Humans will usually consume the output in the form of a report or as a dashboard. The reports can be presented as a file saved on a server, sent directly to a mobile phone, or sent as an email. The dashboard can either be a custom-built dashboard such as R Shiny or plotly dash, or a dashboard view in a company's current dashboard software such as Microsoft PowerBI or tableau. The output of an analytical artifact, which is processed via a data pipeline, can be consumed by many applications; examples are statistical demand forecast integrated into the business workflow of an APS or ERP system, visual quality inspection for a quality inspection agent, and manufacturing alerts consumed by an MES system. The data from both the human consumption and data pipeline can be stored in either the data warehouse or data lake as needed.

6.4.2. Exploitive instantiation

The purpose of exploitive instantiation is to automate as many of the IT processes, as possible by automating and optimising the deployment and integration of pre-constructed analytical artifacts. The instantiation is based on the previously presented approach, where deployments can be done in both the layer of innovation and the layer of differentiation. The exploitive framework is presented in *Figure 16*.

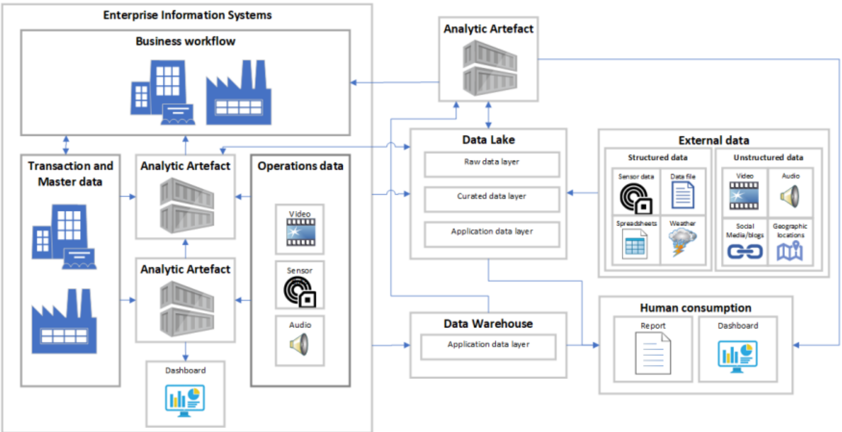

Figure 16. Exploitive framework for integrating analytics with EIS.

In this framework, it is assumed that business-relevant analytical artifacts have been constructed and need to be integrated with the EIS business workflow. It is important that the integration of analytical artifacts can be done in an automated way and that the integration of analytical artifacts can be used with and without an internet connection. The reasons for this are that receiving data over the internet comes with latency that is too large for some applications and because a company or manufacturing site must not be impacted in the event of internet disruptions or fallouts. Consequently, analytical artifacts need to be able to be deployed in both local networks and the cloud. Thus, analytical artifacts that depend on fast reliable data are deployed to the internal network of the EIS, e.g. as an edge computing artifact, into the internal business workflow processing the transactional and operational OLTP data of the enterprise. Artifacts that do not require fast data processing are deployed to a private or public cloud, where management of the artifacts is significantly easier.

The data foundation for the exploitive framework is almost the same as for the exploratory framework. However, some dependencies have been removed, such as access to local data files and the removal of the temporary data layer. These dependencies have been removed, as there is no room for exploration and as such any data that has been evaluated to be relevant needs to be curated to the curation layer or the application data layer and stored appropriately either in the data warehouse or data lake.

In the framework, analytical artifacts are deployed as containers, where they receive data as input and transform the data into an output. If the output is to be used for non-real-time analytics, such as reports or dashboards, the analytical artifact will send the processed data back into the curated data layer of the data lake, and in some instances will send a report directly to a user from the container. In cases where an analytical artifact provides input to an EIS workflow process that is not dependent on real-time data, such as updating a production schedule or updating a statistical demand forecast, the data is stored in the application data layer of the data lake. However, for cases where the application of an analytical artifact is dependent on real-time data, the analytical artifact will both send the data to the database of the EIS in a local network, preferably deployed as an artifact using edge computing, and when available send the data to the data lake.

It is possible to have one or many analytical artifacts both in the cloud and integrated into the individual EISs. The analytical artifacts can also be integrated, where an input to one artifact is the output from another artifact. The configuration and deployment of analytical artifacts will be unique for each company and quite possibly for each EIS within the company. The number of analytical artifacts can potentially grow large, but can be managed and orchestrated by open-source software such as kubernetes.

6.4.3. Ambidextrous instantiation

The two presented frameworks represent two important aspects of ensuring the creation of value from using and integrating analytics with EIS for an O&SCM company. However, it is not recommended to have two different analytical frameworks implemented, which is why there is a need for a combined ambidextrous framework. The framework presented in this section therefore combines the approach and identified mechanisms of the value framework into one final framework, which is presented as *Figure 17*.

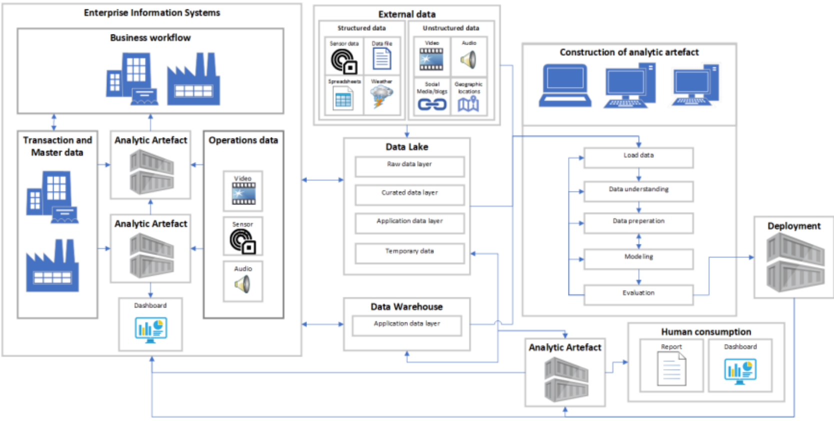

Figure 17. Ambidextrous framework for integrating analytics with EIS.

The combination of the frameworks can, from an IT perspective, be done by simply adding and combining all the processes from the exploratory and exploitive framework. However, the use of the framework must use exploratory processes for exploration and not be limited by the requirements for exploitation. When an analytical artifact is being constructed, speed of development and iterations are important, which means that the deployment of a container should not have to wait on having to spend time on automating data extraction, for example, such as constructing an API to get transactional, master or operational data from the EIS. Additionally, if the integration of external data into the data lake will be time consuming, for exploratory purposes, the best course of action will be to load the data locally into a working station. The evaluation of the artifacts should mainly receive data from the data lake, data warehouse, external data, or a local data file. On the other hand, when conducting an exploitation of an analytical artifact, automation becomes important, and making sure that data can flow automatically becomes essential. In the latter case, speed is not as essential, where the analytical artifact can be deployed either in the cloud or in a local environment. However, the location of deployment of the analytical artifact matters, where two things in particular should be considered. First, the artifact must be integrated within the OLTP processes of the EIS business workflow if the output of an analytical artifact is needed in near-real time. If the analytical artifact can be based on OLAP data, i.e. batch data, the deployment of the analytical artifact depends on the lifespan of the artifact. Artifacts with a lifespan shorter than 12 months should be deployed in a local or public cloud (innovation-pace layer), and artifacts with a lifespan of more than 12 months should be more tightly integrated into the EIS business workflow as the layer of differentiation.

The presented framework deals with all the previously mentioned issues of integrating analytics and EIS, and takes the identified mechanisms and CSF into account. The framework shows how to integrate two different approaches in a loosely coupled architecture aiming at increasing value discovery, the analytic value intersection, and value creation. The frameworks show how heterogeneous IT systems can be used for analytics by sending the data to a data lake or data warehouse, for which a capable worker can transform the heterogeneous data into insights and actions. The artifacts can be scaled by constructing the artifact centrally and deploying the artifact into one or more locations in a lightweight, independent deployment in the form of a container. The artifacts can be integrated with the EIS workflow by either integrating the artifacts with APIs that receive and send data directly from the EIS databases or a data warehouse or data lake. The outcome of the artifacts can either be input into a data pipeline interacting with the EISs or another artifact or for human consumption in the form of a report or dashboard. The framework makes use of currently available software and technologies, where all the software is open-source, except for some databases and EIS.

The purpose of creating an approach and instantiating it into an exploratory, exploitive and ambidextrous framework was twofold. The purpose was to first demonstrate how the value framework *can* be used in a practical setting. That is, the presented instantiations are examples of how the value framework *can* be used in practice. The instantiations are therefore instrumental representations of the conceptual value framework. The author hopes that by presenting instantiations of the value framework, both academics and practitioners will have a better understanding of how to use the identified mechanism for increased value via the integration of analytics with EIS for the O&SCM company. It is not believed that all companies will be able to successfully implement the proposed frameworks, as the configuration of company-specific instantiations relies on many unique factors. However, the value framework and approach are intended to guide practitioners and academics to successfully use the identified mechanism for increased value generation.

The second purpose was to test the value framework in a real environment, where the findings are truly tested as recommended by Pries-Heje, Baskerville, and Venable (2008). The outcome of this approach is that the research is hopefully more trusted and understandable. While the value framework has partially been tested by the instantiations, “the real proof of pudding” is shown once it has been used in a real environment (Pries-Heje, Baskerville, and Venable 2008). Consequently, the next section presents two demonstrators where the ambidextrous framework is used in two cases. The first case is a demand planning case using sales and forecasting data, and the second case is based on the integration and construction of an analytical artifact in a manufacturing site.

6.5. Demonstrators

This section presents two demonstrations of the previously described approach and frameworks. The first demonstrator constructs and integrates the forecast value-added concept into the demand planning process, whereas the second demonstrator integrates an analytical artifact into a manufacturing process, based on article 3. Both demonstrators have been conducted at Arla Foods. The demonstrators are introduced with a section describing current issues in the use of analytics within the respective EIS modules addressed, which is followed by a presentation of the case work. The demonstrators show how the application of the approach and framework can be fitted to a specific use case, where insights and actions can be generated and integrated into a business workflow.

6.5.1. Integrating analytics and demand planning demonstrator

The purpose of the demand planning process is to forecast or predict the future sales of a company as a sales forecast. The sales forecast must consider not only the volume, but also the mix of sales, i.e. which products will sell how much in which market or chain. The process is usually conducted by processing historical data into a statistical forecast, which lays the foundation for the sales forecast process. The statistical forecast can then be modified by making manual changes by a demand planner, for example, if they possess market data that are not used in the statistical forecast. In principle, there is no limit to the amount of changes that can be made to the statistical forecast, where an example of calculating a final sales forecast is presented in Equation 1.

$$\begin{aligned}&Final\ sales\ forecast =\\&Statistical\ FC +\\&Promotion\ FC +\\&Manual\ Changes\end{aligned}$$

Equation 1 - Sales forecast example

The demand planning process is most often conducted in the APS or ERP modules, which mostly have access to internal historical data such as different versions of sales orders, such as confirmed, fulfilled, or promised sales orders. However, these modules often do not have access to data about external factors, such as actions from competitors or drift in consumer demands, which can be an issue when predicting future sales. Additionally, both the APS and ERP modules often lack access to state-of-the-art analytical methods, which is essential in providing state-of-the-art statistical forecasts. In essence, the complexities of the company’s environment cannot be captured in the current state of ERP or APS modules, where changes in the environment are met by manual changes by the companies’ demand planners.

However, introducing analytics into the demand planning process flow can overcome these issues. An example is presented in *Figure 18*, where a classic demand planning process is depicted on the left side, and a depiction of how analytics can improve the demand planning process is depicted on the right. In the example, the overall demand planning process has not been changed. However, the use of mathematical methods has been replaced by an analytic artifact, which can make use of internal and external data and make use of state-of-the-art analytical models. The outcome is a statistical forecast that incorporates data, not only about the company, but also data about the environment in which it interacts. This can be made possible by having workers with the right capabilities and access to the right internal and external data. Thus, it can become possible to calculate how competitor promotions affect the sales of the company or consider the cannibalisation within the company's own products and adjust the statistical forecast accordingly. The outcome is a statistical forecast that better reflects the market condition of the company, which relieves the demand planners to account for these effects.

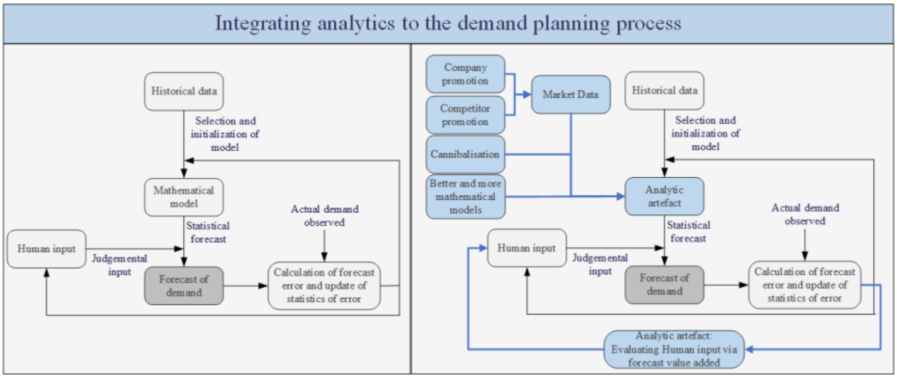

Figure 18. Example of integrating analytics and a demand planning process model – Left side is the demand planning process flow from Silver, Pyke, and Peterson (1998). Right side presents an integration of analytics with the demand planning process flow.

The introduction of analytics, however, can not only improve current processes, but also introduce new processes to the demand planning process flow. In this example, the concept of forecast value added (FVA) (Chybalski 2017) is added to the process. FVA is a method that can be used to analyse the performance of demand planners when adding or removing value to the final forecast, often in the form of a report. That is, do changes to the statistical forecast make the final forecast better or worse than the actual sales amount? The demonstrator in this thesis will present how the integration of analytics can be done by integrating the use of FVA with the SAP APO at Arla Foods.

6.5.1.1 *Presenting the demand planning demonstrator*

The purpose of this demonstrator is to show how the FVA process can be integrated with the SAP APO system at Arla Foods by the use of the approach and frameworks presented in this thesis. The demonstrator uses the exploratory analytics processes for constructing the initial analytical artifact, where this section is concluded by presenting how the finished analytical artifact can be exploited. An overview of how the FVA concept is introduced to the demand planning process is depicted in *Figure 19*.

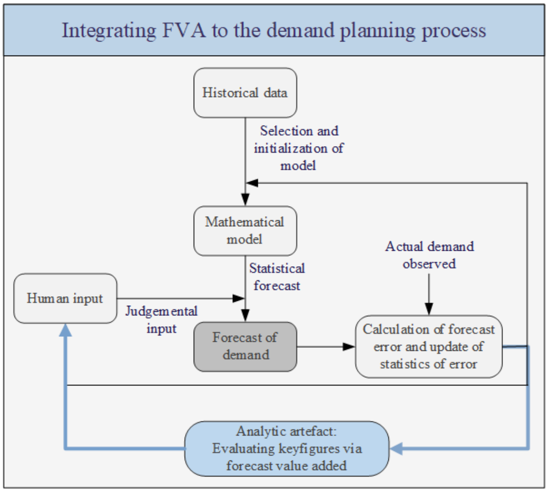

Figure 19. Forecast value-added demand planning process. Modified from Silver, Pyke, and Peterson (1998).

The concept of FVA is to evaluate if the changes made to a forecast are adding value to the forecast or not. FVA is meant to be used as a part of a LEAN process to continuously learn and optimise the process of generating a final sales forecast. Arla Foods makes use of S&OP to manage the sales forecast process, and the company evaluates its sales forecast once a month.

Calculating the FVA is easy in principle, as the calculation is either adding or subtracting sales figures with the sales forecast or changes to the sales forecast. However, it should be noted that the number of periods, e.g. days or weeks, to predict can vary by product group, product or customer. This is referred to as the forecast lead-time and is often dependent on the freeze period of manufacturing a product. Consequently, sales data and forecasts are made and recorded for each period, where the comparison of value added must be related to the forecasted lead-time period. Therefore, the data needed for calculating the FVA are sales data, statistical sales forecast, changes made to the statistical sales forecast, and the final sales forecast for every period.

The SAP APO system used by Arla Foods stores the forecast and sales data into ‘keyfigures’, which is a wide time series representation of data such as sales by time and statistical forecast by time. The keyfigures used in this demonstrator are sales, demand planner adjustments, and promotions, where the data is from the first quarter of 2018 for a specific product group. For this demonstrator, these keyfigures were exported from SAP APO to an Excel spreadsheet and CSV file, which were loaded into a virtual machine. The virtual machine was pre-loaded with the relevant open-source software, in this case the statistical programming language R. The exploratory process is depicted in *Figure 20*.

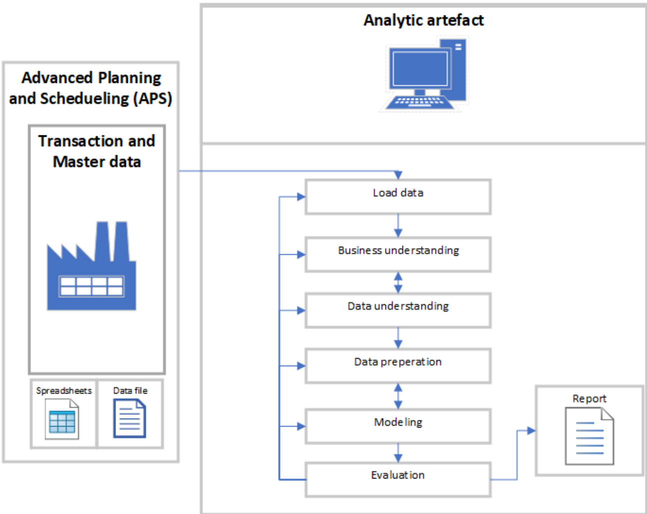

Figure 20. Explorative demand planning demonstrator.

The data were loaded into an R-environment and processed according to the FVA processing steps. The processing of data was conducted into an R-markdown document, which is an HTML file that can be used as a report. The HTML file can be embedded with interactive plots, which were used in this demonstrator.

The process of extracting and processing the data and producing the R-markdown document took less than three days, which provided the company with new valuable insights. It was found that on average, the adjustments to the statistical forecast made by the demand planner in general made the forecast worse (see *Figure 21*). The figure shows how the adjustment to the statistical forecast in week 1 of 2018 added or removed value from the forecast in respect to lead-time 1 to 4.

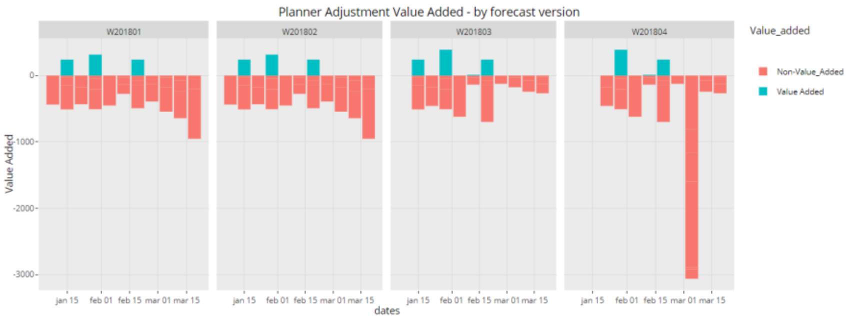

Figure 21. FVA planner adjustments.

Additionally, it was possible to segment the figure into a customer and product level (see *Figure 22*), where it is possible to identify which products and customers generated the biggest positive and negative FVA values. The legend of the figure has been removed for confidentiality reasons, but each dot in the figure should be read as a specific product at a specific customer. The analysis was not conducted on the individual demand planner for ethical reasons; however, there is no technical reason for not doing so.

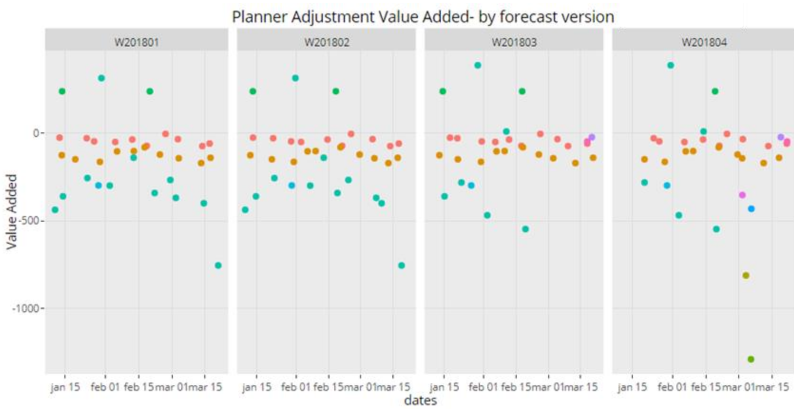

Figure 22. FVA Planner adjustment on customer and product level.

Further, it was also possible to evaluate the impact of promotions on sales, which generated overwhelmingly positive FVA value (see *Figure 23*).

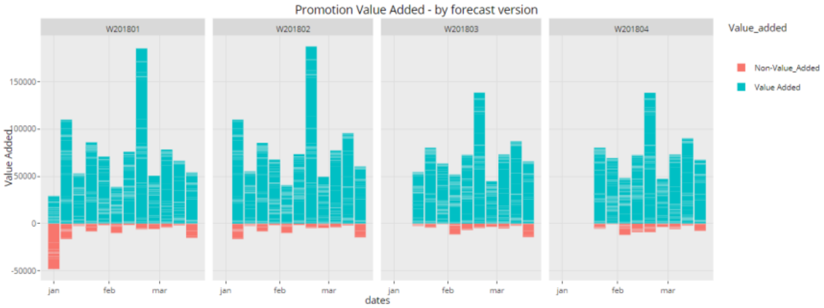

Figure 23. FVA promotion.

It was also possible to do the same analysis on customer and product (see *Figure 24*), which shows that most of the value generated to the forecast is generated by a few product/customer combinations.

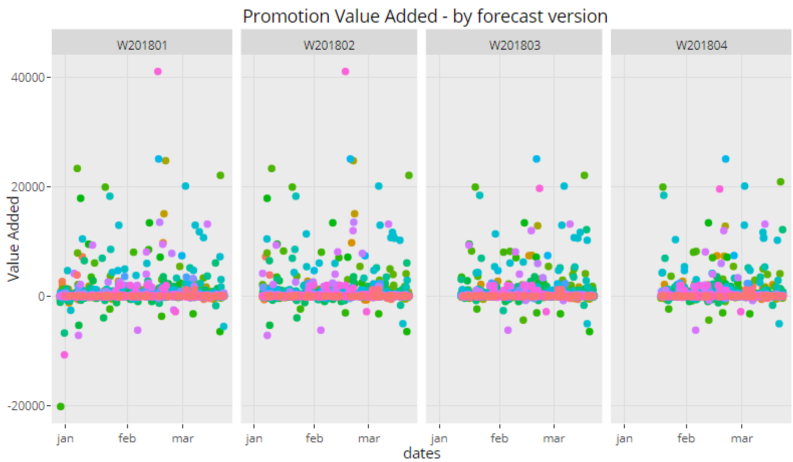

Figure 24. FVA promotion at customer and product level.

Having generated the report ends the exploratory phase of this demonstrator. The process from start to end took less than three days and provided the business with information that they did not have prior. The advantage of using open-source software is that the data could be quickly curated into a form that could be processed by the FVA method. Further, R provides a rich environment of visualisation methods, which simply is not available in the company's APS system. If the same task had been done within SAP, would require that SAP specialist, would have to write new macros to generate a new dataset, which can be cumbersome and costly, and without the possibility of providing an acceptable degree of visualisation of the data. The R-markdown file can be sent via email or stored on a server, where it can be read offline for all users. The R-script that processes the data and constructs the R-markdown report is located on the virtual machine, from where the file is distributed. Thus, in the exploratory phase, it was not necessary to deploy a container.

The demonstrator never moved on from the exploratory phase, where the company was satisfied with the provided solution. However, if the FVA solution was to be automated, a likely solution would be as depicted in *Figure 25*.

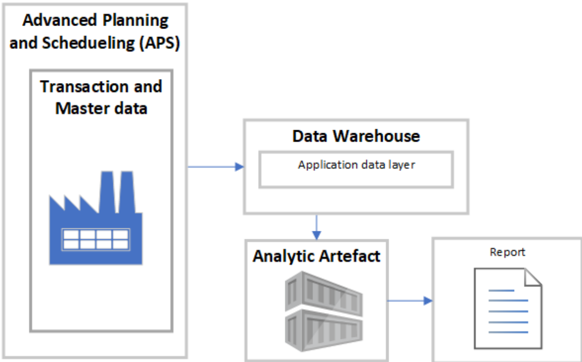

Figure 25. Exploitive demand planning demonstrator.

As the report is only needed once a month, batch processing of the data is sufficient. The analytical artifact that was constructed in the exploratory phase is deployed in a container, which likely will read the data from a data warehouse, because all the keyfigures have been processed into an application-ready data format. The data is then processed by the analytical artifact in the container, which stores the report in a shared file directory, which relevant users have access to.

6.5.2. Integrating analytics with manufacturing demonstrator

The purpose of manufacturing is to convert raw materials into either finished or semi-finished goods. The manufacturing process is managed by creating production plans and schedules either in the APS or ERP modules, which is exported to the MES module, which manages the execution of the plans and schedules. The execution of manufacturing a product is based upon the use of production recipes. A production recipe defines how a product should be produced by stating how the machine settings should be for each manufacturing process and specifies which, where and how much of a material to add to each process.

However, it can be difficult, in a real-world setting, to follow such a production recipe, where many unaccounted factors can impact the production, such as human errors, changes in room temperature, or machine breakdowns. In such cases, it is up to the operators or a manager to give their best guesses into how to best produce a product with as few quality defects as possible. This was observed to be a particular issue in the dairy industry, where each batch of cheeses behaved differently depending on factors such as room temperature and activity of the culture added.

In these instances, analytics can aid in dealing with the complexities that arise from the unaccounted factors. An example of this is presented in *Figure 26*, where an analytics artifact is integrated in the manufacturing execution process. The analytics artifact will take the manufacturing process data for each production process and update the manufacturing recipe, which ultimately means that each production batch has a unique production recipe. The case in article 3 deals with this exact issue, where an analytical artifact was successfully constructed and deployed.

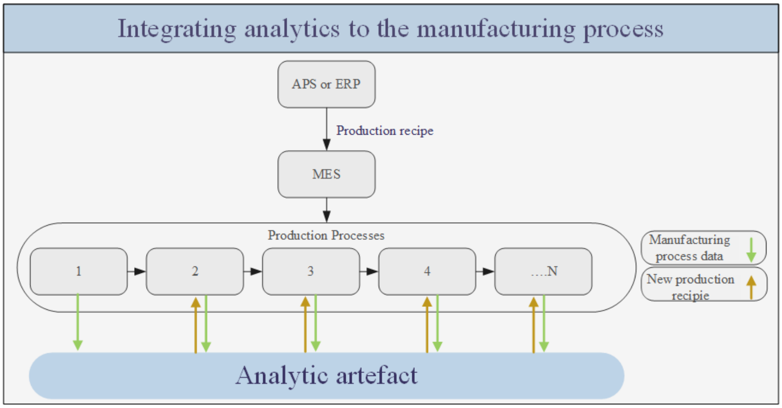

Figure 26. Example of integrating analytics with a manufacturing process.

6.5.2.1 *Presenting the manufacturing demonstrator*

The demonstrator in this section presents how an analytical artifact can be constructed by the use of the exploratory framework, to later be integrated by the use of the exploitive framework. This section describes the process of constructing the artifact and how the approach and framework were used to construct and deploy an analytical artifact in a manufacturing site.

The manufacturing site in this case is a dairy producing blue cheeses. The dairy has found that it is difficult to understand why some cheeses have quality defects and others do not. Consequently, the workers at the dairy are finding it difficult to lower the number of produced cheeses with quality defects. This is a particularly difficult task in a dairy, as the production of cheeses is highly complex, as a cheese is a ‘living product’. The production of a cheese is impacted by the quality of the milk, the activity of the culture added to the milk, and the time for which it takes to produce the cheese in the different manufacturing stages.

The first attempt at creating the analytical artifact aimed to construct a model that could predict which cheeses will have quality defects and prescriptively recommend actions for negating these quality defects. The first step was to get an overview of the production processes, which is depicted in *Figure 27*, and find where and how much data was recorded and stored.

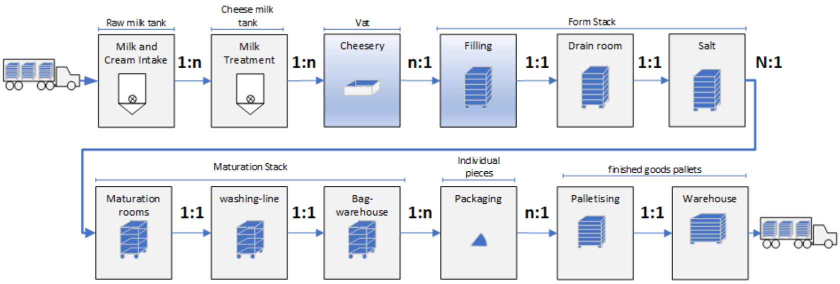

Figure 27. Overview of production processes (Asmussen, Jørgensen, and Møller 2020).

To be able to create an analytical artifact that can predict the quality of cheeses, two types of data were sought. One is the predicted value, which in this case would be data on the final quality of the produced cheeses, and two is the process data recorded during the manufacturing processes, which will be used to train the analytical model.

The final quality data of the cheeses is stored in the palletising process just before being sent to the warehouse. The data were stored in both a local database and in Excel spreadsheets. The data in both storage locations were structured data, which had a key linking the data sources together. The data was extracted from the database and Excel spreadsheet and sent to a local laptop, where the data was curated. The next step was to find the manufacturing process data. The process data was stored in local databases and Excel spreadsheets, where the data in a similar fashion were sent to the local laptop. However, in the process of curating the data, there was an issue with the process data: there were many missing values due to data being recorded by sampling. Only 6.5% of the pallets had recorded data for all the manufacturing processes. Additionally, there were no data recorded from the salt process stage to the palletising process, which from a time perspective cover a large portion of the total manufacturing time. However, despite these constraints, the modelling process was started. While modelling, many approaches were attempted, where different predictive analytical models were applied to the data, which were curated in many ways. However, in the end, it was not possible to construct a model to predict the outcome of cheese batch production with sufficient accuracy. While the outcome of the first iteration of constructing an analytical artifact was a failure, it did not cost much in either direct expenses or time consumed. It was relatively fast to iterate on the data and models, as both the needed software and processing power were available. Further, any issues or clarification about the data or use of data was solved quickly by sending an email or calling the workers or managers of the dairy.

The exploratory process was restarted as a consequence of the failed modelling phase, where a new iteration of the understanding business and data phases was begun. Thus, the scope of constructing the analytical artifact was changed to have a better fit with a business-relevant issue and the available data. The workers and managers at the dairy recommended creating an artifact that predicts the 24-hour pH value, which is estimated to be important for the final cheese quality.

The 24-hour pH value is stored in the filling process, where the selected manufacturing process data used to predict the 24-hour pH value is stored in the cheesery and filling manufacturing areas. The data used for this iteration were structured data stored in local databases, CSV files, and Excel spreadsheets. The model was constructed over many iterations, where the final analytical artifact provides a prediction for the 24-hour pH value with a low prediction error, a prescriptive recommendation model, and the use of explainable AI (xAI) to communicate how the model makes decisions. The artifact is depicted in *Figure 28*.

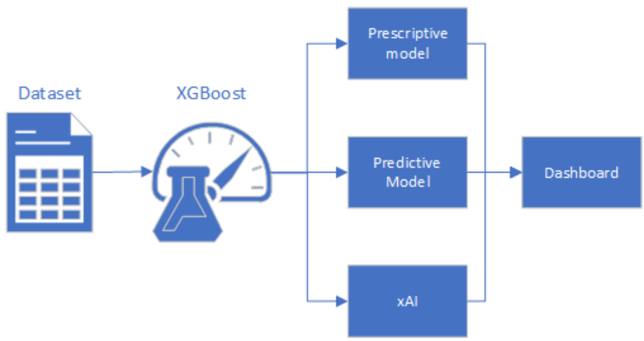

Figure 28. Manufacturing analytic artifact (Asmussen, Jørgensen, and Møller 2020).

The artifact was deployed as a dashboard using the open-source framework R Shiny, which was deployed in a local cloud, where both the researchers and workers of the dairy could access the artifact. The entire workflow and use of the explorative framework in this case is depicted in Figure 29. For further details about the artifact, (see Asmussen, Jørgensen, and Møller 2020).

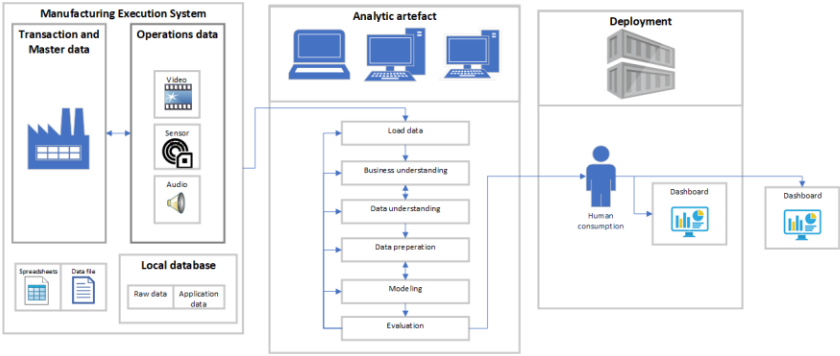

Figure 29. Explorative manufacturing demonstrator.

The use of the explorative framework enabled the construction of an analytical artifact that fulfilled a business-relevant issue, with a short construction time using available data and open-source software. Thus, the framework allowed a sufficient amount of flexibility in constructing an analytical artifact to provide a business-relevant solution, using state-of-the-art analytical methods, at a low cost.

At the time of constructing the analytical artifact, Arla Foods was in the process of establishing a data lake, which means that there was not a lot of data in the data lake to deploy the analytical artifact to. However, it would be relatively easy to deploy the analytical model into a container, which streams the data from a data lake. The R Shiny dashboard in the container can be accessed by any computer to display the dashboard for the workers or managers at the dairy, either at their working desks or at monitors located in the production areas. However, a likely deployment would like the one depicted in *Figure 30*.

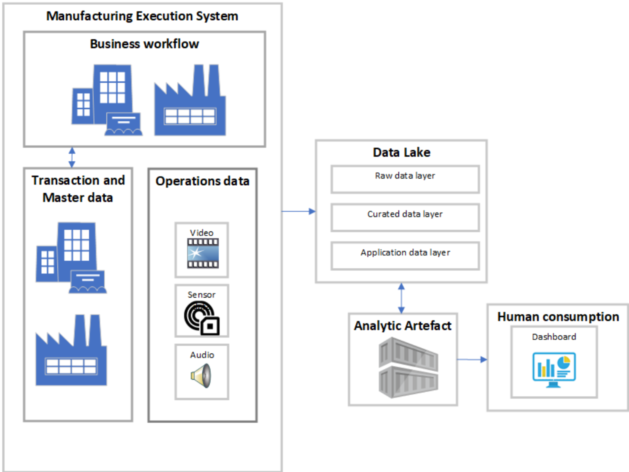

Figure 30. Exploitive manufacturing demonstrator.

The deployment of the artifact has been chosen to not integrate directly with the MES, as there is a need for the manufacturing site to see the model in action and gain experience and trust in using an advanced analytics model. The artifact was therefore deployed in the cloud, where the workers and managers at the site can learn to apply the model and possibly continuously improve the artifact until it is ready for use in day-to-day production. Therefore, a fully automated integrated solution was not sought, as experience with other non-technical issues, such as change management, needs to be dealt with beforehand. If such an integration is to be done in the future, a preferred strategy would be to deploy the container in an edge computing container which streams the data from the MES databases to ensure speed and reliability.

This demonstrator shows how MES can be enhanced by the use of advanced analytical methods by constructing and deploying an analytical artifact. The outcome of constructing the artifacts was unknown before beginning, where the framework allowed the researchers to have enough flexibility to manage the uncertainties that most construction projects will encounter. In this instance, the analytical artifact was seen as a PoC and is treated by the company as such. Therefore, the lifespan of the artifact is lower than 12 months, and consequently was not implemented into the differentiation layer, i.e. deployed directly into the local manufacturing sites' IT systems.

The two demonstrators presented have shown how the value framework and approach of this thesis can be used and modified for specific purposes. While addressing the value mechanisms can be done in many ways, the proposed approach of this thesis is based on the idea of moving the data processing out of the EISs to either local laptops, workstations or cloud solutions that receive data from a data lake or data warehouse, where a full range of open-source software applications can be used to construct models that solve a business-relevant issue. While external data was not used in these demonstrators, they could have easily been used by either receiving a data file or by reading the data through an API. The construction of an analytical model can be done through quick iteration cycles, where data and state-of-the-art software are easily available for a capable cross-functional team consisting of IT, analytical and data management capabilities, with access to domain knowledge. Once a model has been constructed, it can be deployed in a container either in a cloud or close to the EIS, e.g. using a local edge computing deployment. By applying this approach, all the advanced analytical models from OR, for example, can be used in companies today, aiding in closing the gap from the promise and practice by the use of analytics.

Chapter 7. Discussion

The purpose of this chapter is to discuss and evaluate the implications, significance and limitations of the research, as well as whether the research sufficiently addressed the main purpose of the thesis. The main purpose of the thesis is to create an understanding of how value can be created from the integration of analytics with EIS in the O&SCM domain. While there is an understanding of what value is within the research themes, there is a lack of understanding of how to create value, i.e. the mechanisms for value creation were not understood. Additionally, a motivation for doing a PhD for the author was to aid in closing the gap from practice to promise, as described by (Jonsson and Holmström 2016). A description and discussion of the research relevance and rigor was presented in section 3.4.2, which mainly focused on the application and design of a methodology. Academic rigor and relevancy have therefore been sufficiently argued, but there is a need to reflect and discuss the academic and managerial implications of the research.

Consequently, this chapter will discuss the findings in this thesis in the following order. First, a discussion on the selected methodology is presented, which mainly addresses the issue of whether DSR is a good fit for addressing the research purpose. This is followed by a discussion of the implications for research and managers, which then is followed by a discussion of whether the gap between promise and practice has been narrowed. The chapter concludes by describing and discussing the limitations of the thesis and presenting recommendations for future research.

7.1. Discussion of research methodology

The reasons for the selection of DSR have been argued in section 3, where the use of the DSR methodology enables the research to be relevant for the three stakeholders of the thesis: Arla Foods, MADE and Aalborg University. DSR enables the researcher to construct analytic artifacts that bring value in use and in learning, where the findings can be compared with the knowledge base. DSR uses a design cycle, where learnings are made in the process of constructing and deploying analytical artifacts and by reviewing the knowledge base. The goal is to create additions to the knowledge base, which is achieved by comparing and combining the findings of constructing and deploying analytical artifacts with the knowledge base.

The selection of DSR was based on the use of the engaged scholarship model (Van de Ven 2007), which is evaluated as a good tool for selecting a research form. The use of DSR has proven to enable the use of and extending the academic knowledge base, as well as make use of and evaluate research in a real environment. This is not a new finding where several authors have concluded that DSR can aid in bridging the gap between theory and practice (Holmström, Ketokivi, and Hameri 2009; van Aken 2004; Sein et al. 2011). However, there are no standard ways of conducting DSR, and as such, there are many ways of conducting and evaluating DSR. As an example, besides the selected research framework of this thesis, (Hevner, March, Park, and Ram 2004; Peffers et al. 2007), the following authors offer different DSR frameworks (Drechsler and Hevner 2006; Göbel and Cronholm 2016; Gregor and Hevner 2013; Gregor, Kruse, and Seidel 2020; Hevner 2007). The many frameworks presented for the use of DSR could indicate a low level of maturity; however, it does allow a researcher to select and make use of the DSR framework that has the best fit for the research. As such, the use of DSR for this thesis gave a lot of research flexibility in two different environments: the university and Arla Foods. DSR aided the research to make the outcome relevant from an academic perspective, which have resulted in three journal papers, and by providing learning and IT artifacts for Arla Foods and the companies in the MADE programme. The most challenging aspect of DSR was the evaluation of the research. Making sure that the research was both relevant and rigorous was particularly difficult, as the author did not find a clear method for how to evaluate DSR. This is despite several authors offering different evaluation methods and metrics for the evaluation of DSR (Eriksson, Åkesson, and Kautz 2011; Prat, Comyn-Wattiau, and Akoka 2015; Venable, Pries-Heje, and Baskerville 2016; Baskerville, Pries-Heje, and Venable 2011; Pries-Heje, Baskerville, and Venable 2008; Sein et al. 2011). While the evaluation framework by (Pries-Heje, Baskerville, and Venable 2008) was used in this thesis, it did require a lot of subjective reasoning. A risk of relying on subjective reasoning is that the evaluation could turn out to be wrong, rendering the research findings invalid. That risk has been addressed by applying the findings of the research to a naturalistic environment. Ideally, the evaluation would have been conducted in several naturalistic environments; however, the author did not have access to more environments. The consequence of only evaluating the findings in one environment is that the findings could potentially be misleading. The evaluation of this thesis found that the research of this thesis had sufficient practical and academic relevance and rigor, but evaluating the findings in more naturalist environments would further strengthen the reliability of the evaluation. While the evaluation framework by (Pries-Heje, Baskerville, and Venable 2008) did rely on subjective reasoning, it was found to aid in structuring the evaluation of the research and ensuring that the most important aspects of evaluation are covered. It is of the author's opinion that it can be quite difficult to properly evaluate DSR research, where more specific evaluation guidelines are needed.

7.2. Research implications

This thesis contributes with knowledge and understanding of how to create value by the use of analytics for O&SCM companies. The thesis presents a more nuanced and detailed view on the creation of value within the research themes, compared to some mostly used value frameworks, such as the framework by Gartner (2012), depicted in *Figure 1*. Thus, the findings of the articles attached to this thesis, as well as the value framework, are considered a contribution to the knowledge base. Additionally, article 2 and Jonsson and Holmström (2016) found that most of the proposed frameworks within the field are mostly conceptual and lack empirical grounding, where the research of this thesis is sought to provide both conceptual and empirical grounding. The research of this thesis addresses these issues, where value mechanisms have been identified and presented in a form that is useable and applicable for both academics and practitioners. To be able to present the research findings in such a form meant that the mechanisms were combined with other related research domains into a value framework and instantiated into an approach and demonstrators. Doing this entails that several decisions had to be made regarding the construction and presentation of the framework, approach and demonstrators. The remainder of this section will discuss these decisions, where first a discussion on value mechanisms is presented, followed by a discussion on the value framework and the presented approach and demonstrators.

7.2.1. Value mechanisms

Most of the identified value mechanisms have been found by reviewing the academic knowledge base by combining value mechanisms from the research fields of big data, O&SCM, analytics and IT, and by exploring new value mechanisms using a design science approach. This thesis therefore contributes with both synthesises knowledge based on the knowledge base and with newly created prescriptive knowledge in the form of a value framework.

A big part of identifying relevant value mechanisms was based on the big data value framework by Brinch (2018), which is based on the research themes of big data, SCM and IT values, and does not explicitly cover the use analytics or EIS. However, it is of the author's opinion that value in relation to big data and SCM is highly correlated with the use of analytics and EIS, where data needs to be processed and managed into a company's processes to be able to create value. That is, data only creates value when it has been transformed by analytics and creates value in learning or use (Herden 2019; Viaene and Van Den Bunder 2011; Larson and Chang 2016). However, to ensure that the three research themes of analytics, EIS and O&SCM have been proficiently covered, have the value framework by Brinch (2018) been extended by incorporating the value mechanisms from IT business value theory, analytics value theory, and O&SCM theory. While recently the theme of big data has had a lot of both industrial and research interest, big data is merely regarded, in this thesis, as a part of the value discovery process in the form of a data ecosystem.

The research on value within the research themes of the thesis was decided to be scoped to not include the value capture aspect. However, the importance for a company to include the perspectives of value capture is essential for success. If the use of analytics does not address a business problem that fits with a company's strategy, it can be difficult to create value for a company even if all the presented value mechanisms in this thesis have been addressed. However, including value capture in this thesis would not only expand the scope of research, but also change the focus of research. The thesis has predominately been taking an IT perspective, where including value capture would introduce other aspects such as overall company strategy. Consequently, for a comprehensive understanding of value mechanisms for a company, the research of this thesis needs to be combined with research on value mechanisms in the intersection of value creation and value capture. Additionally, more research could be done on the starting point of analytics, where the research of this thesis has only been conducted from a problem-first starting point. A data-first approach rarely creates value (Herden 2019); however, there has not been much research on business-first starting points.

Last, while the use of CSF enables a more operational perspective of the value mechanism, they are still very broad descriptions, where a practitioner or academic needs knowledge within many areas, including IT, O&SCM, analytics and EIS, to make use of the CSF. Consequently, the CSF and value mechanisms must be seen as a first step to truly enable both academics and practitioners to take full advantage of the rising volumes of data and advanced analytical methods.

7.2.2. Value framework

The purpose of the value framework was to combine the value mechanisms and CSF into a single framework which operationalises the creation of value within the research themes of the thesis. This section discusses to what degree that has been achieved, as well as discusses if and how this could have been done differently.

The value framework presents an extensive overview of the research themes of value mechanisms in the intersection of value discovery and value creation, combining both prerequisites, such as managing heterogenous data and IT systems, with the need for specific human capabilities. However, for research to be applicable to practitioners, it also needs to be actionable (Christensen and Raynor 2003; Halldórsson, Hsuan, and Kotzab 2015; Jonsson and Holmström 2016). While the value framework does present the value mechanisms and group-related mechanisms, there are still additional steps for a company to implement a solution based on the value framework. For example, while the framework stresses the importance of human capabilities, understanding and identifying specifically which capabilities are needed are not explained. Further, while it is essential to cross the data barrier, there are likely many more parts of the data barrier that have not been identified. Data quality would also likely have an impact on the potential value generated by the use of analytics and thus needs to be considered. As a consequence, the approach and demonstrators were presented to show how the value framework could be used. However, the approach cannot be seen as universal; as such, there is still a need for companies or researchers to create approaches based on the value framework. Thus, while the value framework does shorten the gap between promise and practice, it does not close it.

Further, the framework is constructed based on the use of the data mining framework CRISP-DM (Shearer 2000). However, the value framework could have been based on other analytics or data mining frameworks. Several analytical process frameworks have since the creation of CRISP-DM been proposed, where an example is the team data science process framework from Microsoft (2021). However, most of these frameworks are based on the same fundamental processes, where it is evaluated that it would not make much of a difference to the value framework to incorporate other analytic process frameworks.

The value framework proposes that there are two routes between the analytic value intersection and value creation: an explorative or exploitive path. The framework distinguishes between addressing unique and non-unique business issues to manage the division between exploration and exploitation. This presents an opportunity to identify business cases where analytical artifacts can be treated either to explore new opportunities in the environment via analytical methods or exploit the analytical artifacts through IT deployment and maintenance workflows. This is a distinctive contribution to the management of analytical artifacts; however, there can be other considerations that need to be considered when deciding whether to explore or exploit analytical artifacts. Further, the decoupling points could also change in the future as more processes can be automated. For example, there is a growing research area to automate some processes in the exploratory phase, such as data cleaning and imputation.

7.2.3. Instantiations of the value framework

In the form of an approach, frameworks and demonstrators do not have the same academic rigor as the value framework. The purpose of the instantiations was to show how to use the value framework; however, the instantiations cannot be seen as generalisable findings. Nonetheless, they do show how to use the value framework and, most importantly, evaluate the value framework in a naturalistic environment. The main reason for showing how to use the value framework was to demonstrate for both academics and managers how to transform the knowledge of value mechanisms into actions that fit within a specific context. While the instantiations may not have the usual academic rigor, they do provide an aspect of actionability that most research is lacking to make it relevant for practice. While it can be difficult to incorporate such instantiations into a journal paper, it was deemed to be essential for this thesis to include to also cater to a managerial audience. In general, I would encourage all researchers to present cases or demonstrators on how to use their research, which could be attached as an appendix to a journal or as a blog post. It is of the authors intend to continue working on a generalisable approach, which potentially could be submitted to address the call for papers by (Abedin et al. 2020).

The instantiations presented are based on the knowledge of the author, and as such, it can be expected that the value framework can be instantiated in many other ways. The author has mostly worked with EIS offerings from SAP and cloud solutions from Amazon and Microsoft, as well as mainly using SQL, R and Python for data science. Other technologies, methods or tools could potentially be used to create an even better approach or instantiations, which is unknown to the author. Concepts other than the one presented could have also been used, e.g. the approach suggesting centralisation of storage and management of data, others believe it should be decentralised as a distributed data mesh (Fowler 2019). While the approach recommends edge deployments, none of the demonstrators used an edge device, which would have been preferred to evaluate the instantiated frameworks naturalistically.

While the instantiations are not seen as generalisable, some aspects are. The integration of analytical artifacts with BPM needs to be based on a loosely coupled integration. It can be expected that analytical artifacts need to be regularly remodelled or reconstructed, as the data or environment changes, which must not hinder the execution or control of business workflows. Additionally, the use of loosely coupled systems enables companies to separate exploratory and exploitive processes to be managed by different teams with different capabilities and responsibilities.

7.3. Managerial implications

A motivation of this thesis was to create research that is practical and thereby actionable for managers and practitioners. The presented research identified the mechanisms for creating value in the research themes of analytics, EIS and O&SCM, where additionally value and competitive prerequisites and enablers have been identified. However, the findings have mostly been presented by the use of an academic language, where this section presents five recommendations to make the thesis more actionable.

7.3.1. Recommendation 1: Separate analytics and BPM

It is recommended to separate the management of business processes and the creation and deployment of analytical artifacts. The management of business processes is done in EIS, which changes at a significantly slower rate compared to the construction and integration of analytical artifacts. By separating the two, enables a company to not create disturbances in their daily operations and analytical artifacts can be created with the most suitable software, as well as enabling easy access to both internal and external data. Further, the implementation and integration of analytics should not be considered as a big bang approach, but instead be integrated based on the identification of individual business issues. Consequently, the integration of analytics into EIS will not be managed as one large implementation project, but by many smaller implementation projects, as a continuous and additional part of a company's processes. Over time, it can be expected that companies will have hundreds or thousands of analytical artifacts deployed and integrated with their BPM. In most cases, this will mean that the integration of analytical artifacts is based on loosely coupled integrations, where the SOA applications of EIS are integrated with analytical artifacts as microservices.

7.3.2. Recommendation 2: Build cross-functional capable teams

The creation of value within the research themes of this thesis is heavily reliant on the availability of the right human capabilities. The systems, data and analytical artifacts must be managed to address company-specific issues. There are many IT offerings and software that can create solutions that fit a company's process, but it depends on having the right human capabilities. As such, a company should hire cross-functional teams that can manage both the exploration and exploitation processes. The identified capabilities needed are IT, data management, and analytical capabilities. It is also essential that a cross-functional team will have access to domain knowledge by either having a worker with domain knowledge within the team or having direct access to a relevant business worker. Specifically, which capabilities are needed is dependent on the individual company and the solution needed to address their specific company's issues. However, both Herden (2019) and Berinato (2019) provide suggestions for how to form a team, e.g. Berinato suggests basing a data science team on having enough talent within the areas of project management, data wrangling, data analysis, subject expertise, design and storytelling.

7.3.3. Recommendation 3: Democratise data science

While typically the construction of IT artifacts has been limited to the IT department, this approach will likely be a bottleneck for companies as the use of analytics matures. Fundamentally, one analytical artifact addresses one specific business issue and thus can each company potentially have thousands of analytical artifacts deployed. The creation of analytical artifacts is not only dependent on IT, but also on making sure the analytical artifact provides valuable insights or actions for the business to act upon. It would therefore be of benefit to decentralise the creation and deployment of analytical artifacts from the IT department to the functional areas, where the analytical artifacts are integrated. The democratisation of data science can be done in many ways, e.g. each functional area within a company will hire its own data scientist or the functional areas analysts are trained to use prebuilt analytical artifacts or make use of low-code applications. For this to be applicable requires that a company has considered the presented value mechanisms of the value framework, e.g. the data from the heterogeneous IT systems should be easily accessible, as well as having access to the right tools and software.

7.3.4. Recommendation 4: Make use of the analytic decoupling point

Companies must make clear and thoughtful decisions on which processes of the construction and deployment of analytical artifacts should be exploratory and which should be exploitive. The exploratory processes are based on the ability to explore and create novel solutions for so far unaddressed business issues by exploring possibilities with the use of data. This requires teams that have an exploratory mindset and have IT, data management, and analytical capabilities, coupled with domain knowledge. On the other hand, exploitation processes are purely focused on being efficient and constructing and deploying solutions, solely based on IT capabilities. It would therefore be wasteful to use exploratory processes, where exploitation could have been used, and at the same time opportunities for value creation can be missed by using exploitation, instead of exploring possible novel solutions to a business issue.

7.3.5. Recommendation 5: Use state-of-the-art open-source software

The final recommendation is based on the current technological offerings and can change in the future. The recommendation is to make use of the state-of-the-art open-source software, as it is not only free to use, but also provides the best analytical and data management methods and frameworks. Further, there are large online communities that share knowledge and experiences in using the open-source software, which provides support for the construction and deployment of analytical artifacts. The open-source offerings are constantly updated with updates to currently available methods and frameworks, as well as providing the newest methods and frameworks. While it is still not the norm, OR journal publications are more often supported by having their methods shared in open-source software. However, it should be noted that companies can both construct and deploy analytical artifacts using proprietary software, where many of the required methods and frameworks do exist. However, they rarely provide benefits over their open-source alternatives.

7.4. Discussion of practice vs. promise

After having described the implications for research and managers, there is a need to reflect and consider whether the research aided in closing the gap between practice and promise. It is evident that academic research needs to make contributions to the knowledge base, but research within the applied sciences also needs to be actionable and understandable for practitioners (Jonsson and Holmström 2016). The research presented in this thesis is mostly written in an academic language, which can be difficult for non-academics to understand. Examples are that the term *artifact* is rarely used outside of academia, where other terms such as *model* or *solution* would often be easier to understand. It has also been of the author's experience that the journal papers and thesis have been difficult to understand for the workers at Arla Foods and the MADE programme, where presenting the findings using other terms and visualisations have made the research more understandable. As a consequence of these experiences, the value framework has been instantiated to aid in communicating how the value mechanisms can be utilised. The instantiations provided an opportunity to evaluate the value framework, but just as importantly, they made the research more understandable for a non-academic audience.

The research of this thesis has therefore purposely been designed and conducted to address an academic and managerial audience. It cannot be argued that the research of the thesis has closed the gap between promise and practice, but it has provided first steps in closing the gap. From an academic perspective, the research has provided additions to the knowledge base by identifying value mechanisms and presenting a value framework. A consequence of the research of the thesis is that by making use of the value mechanisms identified in this thesis, academic work can be integrated into a company's business processes. If researchers share their code from their research papers, enables companies to make use of newly created state-of-the-art analytical methods and use that to construct and deploy analytical artifacts in novel ways to address a company business issue.

7.5. Limitations

The research of this thesis was subject to three main limitations, which are discussed below.

7.5.1. Not considering value capture

The creation of value depends on the three value perspectives of value discovery, value creation, and value capture. Thus, for companies to create value, they need to identify business issues that fit with the company strategy and can be addressed using the available enterprise or external data. This thesis only covers the intersection between value discovery and value creation, and as such, there are likely other mechanisms that need to be accounted for to create value and make companies more competitive.

7.5.2. Long-term implications

The research of this thesis is mostly based on low-maturity companies, where there are either no or a low amount of advanced analytical artifacts deployed. Consequently, many of the long-term implications have not been considered or researched. Looking at industries other than where typical O&SCM companies are located can elucidate some challenges that these companies can face. An example is the paper by Sculley et al. (2015), which is written by employees at Google, where they share their experiences of having deployed thousands of advanced analytical artifacts. They argue that the construction of these artifacts is only a minor part of managing advanced analytical artifacts, where most of their efforts are on the IT infrastructure, such as monitoring, machine resource management, process management tools, feature extraction, data collection, and data verification. Further, in an industry survey, Davenport (2018) finds that it is easier for companies to develop models than to integrate and deploy solutions. As O&SCM companies become more mature, they will likely face some of these challenges, which this thesis does not address.

7.5.3. Design limitation

While the research of this thesis is grounded in the knowledge base, the design cycle of the research has been limited by the author's understanding and knowledge of the research themes. Additionally, the design and evaluation of the research has only been conducted at Arla Foods, which does not make a representation for all companies. The design of the artifacts has likely been impacted by the problems, knowledge and IT systems of Arla Foods. However, before doing the Ph.D., the author worked with state-of-the-art analytical methods in a start-up company and was an SAP consultant for four years, which provided knowledge of analytics and O&SCM application for other businesses. However, the knowledge of the author within EIS is mostly based on SAP, which presents a research limitation. While the design process has been impacted by these limitations, both the author and workers at Arla Foods have been in contact with other O&SCM companies, where the findings of the research were communicated and compared.

Further, even though the value framework was evaluated in a naturalistic environment, not all parts of the instantiations were evaluated. Specifically, the evaluation of deployment of the artifacts were limited. Further, several aspects that have been identified as important for analytical artifacts have not been demonstrated, such as integrating the use of external unstructured data. Although the research did not specifically evaluate these limitations, they are simply seen as a part of the analytics toolbox, where the analysis of unstructured data uses other methods provided by the open-source software solutions.

7.6. Recommendation for future research

The research presented in this thesis contributes with new knowledge within the thesis research themes; however, there are several avenues for future research, where five main research directions are identified.

7.6.1. How to identify analytical, IT and data management capabilities

One of the most important aspects of obtaining value from the use of analytics within the domains of EIS and O&SCM is based on the availability of the right human capabilities. This thesis found that for a successful analytics project, IT, data management, and analytical capabilities are needed. However, the research does not specify precisely what capabilities are needed for which projects. For example, different analytical projects will have different requirements for analytical capabilities, where analytical projects may require capabilities within the fields of simulation, Bayesian statistics, or neural networks. Similarly, required data management capabilities can be different depending on the need to create a company data platform or simply create SQL views. While there has been research within this topic, (Herden 2019; Berinato 2019), more is required.

7.6.2. Data barrier

Moving from data discovery to the analytic intersection required that data be organised and prepared to accommodate the use of analytical modelling. This is in the value framework coined as the data barrier. The research of this thesis found two data requirements for the data barrier, which are data needs to be traceable and able to be aggregated into the desired level of analysis. However, the research in this thesis is mainly based on the use of analytics within manufacturing, and thus there is further need to study requirements for data in other contexts and environments.

7.6.3. Evaluating the value framework in more environments

The value framework is constructed based on a design process which combines the knowledge base with the environment of Arla Foods. However, the generalisability of the findings cannot be guaranteed, and it is therefore recommended to study the use of the value framework as well as evaluate the value mechanisms in other environments.

7.6.4. Researching analytic decoupling points

A central part of the value framework is the concept of analytic decoupling points. The usage of analytical decoupling points provides a tool to identify when to make use of exploratory or exploitive analytical processes. The concept is fundamental in navigating the dilemma of when to explore opportunities and when to exploit the company's resources. However, while analytic decoupling points are central to the value framework, they still need to be researched in other contexts. Researching the analytic decoupling points in other contexts can provide further validation of the concept and identify further developments and improvements.

7.6.5. Research self-service analytics

Last, while there is great promise for the democratisation of data science, there is still little knowledge on how to achieve this for the O&SCM companies. The democratisation of data science is a vast research area, covering research themes such as automated machine learning, low-code development, and making access to relevant data easy (Deloitte 2019). While, the author acknowledges that all of these research themes are important, the role of self-service analytics is identified to be of particular importance for the integration of analytics in O&SCM companies. The integration of analytics is best done as small projects, constructing and deploying purpose-built analytical artifacts, based on domain knowledge. Consequently, if the construction and deployment of analytical artifacts can be enabled for all O&SCM functional areas, it would enable companies to truly extract value from their enterprise data.

Chapter 8. Conclusion

This thesis set out to explore and identify how value can be created by integrating analytics with EIS in the O&SCM domain. While there has been research on defining value within these research themes, there is a lack of research on how to create value. The research areas of the thesis are viewed as applied research, and thus was the aim to not only do conceptual research, but also ground the research in naturalistic environments by the use of DSR. Thus, the research of this thesis was structured to do research applicable to both an academic and managerial audience.

As a consequence, two research objectives were derived, which are presented below.

Research objective 1: *To identify the value mechanisms at the intersection of value discovery and value creation by integrating analytics with EIS.*

Research objective 2: *To create an approach based on the value mechanisms in the intersection of value discovery and value creation by integrating analytics with EIS*.

The first research objective aimed to identify the value mechanisms within the research themes of the thesis. This was done by conducting a literature review in article 2 and by applying an ADS approach in article 3, where an analytical artifact was constructed and deployed in a real environment. Further, the findings of the two articles were synthesised and compared, which resulted in the identification of value mechanisms and CSF in chapter 4. However, it was found that the literature review did not sufficiently address important aspects of value generation, and there was subsequently a need to relate the research finding with the related research fields of analytics value theory, IT business value theory, and O&SCM theory. The result was a value framework that combines the research findings of value mechanisms and CSF with the mentioned research themes. The value framework relates the findings of value mechanisms with the analytics process, governed by the CRISP-DM framework, and the value definitions of value discovery, the analytic value intersection, and value creation. There are different value mechanisms for the three value stages, which is reflected in the value framework presented in chapter 5. Further, a central part for the creation of value was found to be based on either facilitating exploratory or exploitive analytical processes. To aid in deciding when to do exploration or exploitation is an analytic decoupling point proposed, which is based on addressing unique or non-unique business issues. The value framework is seen as the main answer to the first research objective. There are several implications and limitations for the value framework, which are described and discussed in chapter 7.

The purpose of the second research objective was to instantiate the value framework, which communicates the research to both an academic and managerial audience, and at the same time evaluates the value framework in a naturalistic environment. An approach was created based on the value framework, which was instantiated into three frameworks addressing an exploratory, exploitive and ambidextrous analytic workflow. Finally, the approach and ambidextrous framework were applied in two demonstrators. In the first demonstrator was an analytical artifact constructed and deployed to integrate the use of the forecast value-added concept into the demand planning processes of Arla Foods. The second demonstrator constructed and deployed an analytical artifact in a manufacturing case, where an artifact was constructed using predictive and prescriptive analytical methods. The second demonstrator was based on the work presented in article 3. The creation of the approach and instantiations both evaluated the findings of the thesis and made the research findings more accessible to a managerial audience. There are several implications and limitations in the creation of the approach and instantiations, which are described and discussed in chapter 7.

The research of this thesis has implications from both a research and managerial perspective. The thesis proposes new additions to the knowledge base by having identified value mechanisms within the research themes of analytics, EIS and O&SCM, and additionally proposes a value framework that integrates the identified value mechanisms with the research themes of analytics value theory, IT business value theory, and O&SCM theory. Furthermore, an analytical decoupling point approach is proposed, which aids in determining when to do exploratory analytics and when to do exploitive analytics. There are many managerial implications from the research of this thesis, where five main areas have been identified. These five areas are presented as recommendations for managers: separate analytics and BPM, build cross-functional capable teams, democratise data science, make use of the analytic decoupling point, and use state-of-the-art open-source software. The five recommendations are described in section 7.3.

The research of this thesis has identified several opportunities for future research, where five research themes are seen as particularly important. These five research themes are: how to identify analytical, IT and data management capabilities; data barriers; evaluating the value framework in more environments; research analytic decoupling points; and researching self-service analytics. A description of the recommendations for future research is presented in section 7.6.

Finally, an overall conclusion of the research of the thesis is that, while it is evident that many companies are finding it difficult to gain value and become more competitive by the use of analytics, it is possible using current technologies, methods, and knowledge to construct and deploy analytical artifacts that create value. However, as many companies have experienced, it is not easy. This thesis has identified value mechanisms that companies should consider when constructing and deploying analytical artifacts. The challenge for companies is to mainly manage people and data. It is naturally essential that any form of analytics requires a data foundation, where specific data requirements are fulfilled. The research within this thesis found that analytics requires that data is traceable across functional and production areas within a company and needs to be aggregated into a desired level of analysis. However, this introduces challenges of integrating and processing heterogeneous data from heterogeneous IT systems. The management of heterogeneous data and IT systems is best done outside of EIS so as to not interrupt daily operations and have access to the right tools and software. Further, the processing of data for analytics is heavily reliant on human capabilities. There are many IT systems that can process data for analytics and make use of advanced analytics methods; however, they all rely on having workers with the right capabilities within the areas of analytics, IT and data management. Furthermore, the availability of domain knowledge is identified as crucial for creating business-relevant analytical artifacts. Additionally, workers need to be clear and thoughtful in managing the exploratory and exploitive analytical processes, where this thesis proposes that it should be managed by the use of an analytic decoupling point. Consequently, a value framework is proposed, which companies can make use to aid in creating value by the use of analytics and hopefully become more competitive.

Finally, a motivation of this thesis was to aid companies and researchers in making use of state-of-the-art analytical methods and integrate them with companies' EIS. The thesis manages to achieve that by providing both additions to the knowledge base in the form of value mechanisms and a value framework, for which practitioners can make use of the value framework and be inspired by the instantiations of the value framework. Therefore, this thesis aids both researchers and managers by presenting value mechanisms, instantiation and demonstrators, which communicate how value is created by integrating analytics with EIS in the O&SCM domain. However, despite having identified the value mechanism, this does not mean that value for integrating analytics with EIS can be ensured. As the creation of value is heavily reliant on human capabilities and the management of company-specific IT landscapes, there is a lot of room for customisation and interpretation of how to make use of the value mechanisms. Essentially, the tools and methods are available for companies to make use of advanced analytical artifacts, but the data foundation, as well as construction, deployment and integration of analytical artifacts, is based on having access to the right human capabilities.

REFERENCES

Abedin, Babak, Iris Junglas, Christian Meske, Hamid Motaharu-Nezhad, and Fethi Rabhi. 2020. “CALL FOR PAPERS Special Issue on: Designing and Managing Human-AI Interactions.” *Frontiers, Information Systems*.

Adler, Paul S., Mary Benner, David James, John Paul, Emi Osono, Bradley R. Staats, Hirotaka Takeuchi, et al. 2009. “Perspectives on the Productivity Dilemma.” *Journal of Operations Management* 27 (2): 99–113. https://doi.org/10.1016/j.jom.2009.01.004.

Akyuz, Goknur Arzu, and Mohammad Rehan. 2009. “Requirements for Forming an E-Supply Chain.” *International Journal of Production Research* 47 (12): 3265–87. https://doi.org/10.1080/00207540701802460.

Altinkemer, Kemal, Yasin Ozcelik, and Zafer Ozdemir. 2011. “Productivity and Performance Effects of Business Process Reengineering: A Firm-Level Analysis.” *Journal of Management Information Systems* 27 (4): 129–62. https://doi.org/10.2753/MIS0742-1222270405.

Appelbaum, Deniz, Alexander Kogan, Miklos Vasarhelyi, and Zhaokai Yan. 2017. “Impact of Business Analytics and Enterprise Systems on Managerial Accounting.” *International Journal of Accounting Information Systems* 25 (March). Elsevier: 29–44. https://doi.org/10.1016/j.accinf.2017.03.003.

Arla Foods. 2020. “Arla Foods Annual Report 2019.” Accessed November 17. https://www.arla.com/company/investor/annual-reports/.

Arora, Tanuj, and Amol Nirpase. 2008. “Next Generation Business Process Management: A Paradigm Shift.” *Proceedings - 2008 IEEE Congress on Services, SERVICES 2008* 1: 81–82. https://doi.org/10.1109/SERVICES-1.2008.54.

Arunachalam, Deepak, Niraj Kumar, and John Paul Kawalek. 2017. “Understanding Big Data Analytics Capabilities in Supply Chain Management: Unravelling the Issues, Challenges and Implications for Practice.” *Transportation Research Part E: Logistics and Transportation Review* 114 (May). Elsevier Ltd: 416–36. https://doi.org/10.1016/j.tre.2017.04.001.

Asmussen, Claus Boye, Steffen Lundgaard Jørgensen, and Charles Møller. 2020. “Design and Deployment of an Analytic Artifact – Investigating Mechanisms for Integrating Analytics and MES.” *Journal of Enterprise Information Systems*, In 2. Review.

Asmussen, Claus Boye, and Charles Møller. 2020. “Enabling Supply Chain Analytics for Enterprise Information Systems: A Topic Modelling Literature Review.” *Enterprise Information Systems* 14 (5). Taylor & Francis: 563–601. https://doi.org/10.1080/17517575.2020.1734240.

Astley, Graham W., and Raymond F Zammuto. 1992. “Organization Science, Managers, and Language Games.” *Organization Science* 3 (4): 443–60.

Ballou, Ronald H. 2007. “The Evolution and Future of Logistics and Supply Chain Management.” *European Business Review* 19 (4): 332–48. https://doi.org/10.1108/09555340710760152.

Banerjee, Arindam, Tathagata Bandyopadhyay, and Prachi Acharya. 2013. “Data Analytics: Hyped Up Aspirations or True Potential?” *Vikalpa* 38 (4): 1–12. https://doi.org/10.1177/0256090920130401.

Barbosa, Marcelo Werneck, Alberto de la Calle Vicente, Marcelo Bronzo Ladeira, and Marcos Paulo Valadares de Oliveira. 2017. “Managing Supply Chain Resources with Big Data Analytics: A Systematic Review.” *International Journal of Logistics Research and Applications* 21 (3). Taylor & Francis: 177–200. https://doi.org/10.1080/13675567.2017.1369501.

Barton, Dominic, and Court David. 2012. “Making Advanced Analytics Work for You - Harvard Business Review.Pdf,” no. October.

Bartunek, Jean M. 2007. “Academic-Practitioner Collaboration Need Not Require Joint or Relevant Research:” *Academy of Management Journal* 50 (6): 1323–33.

Baskerville, Richard, Jan Pries-Heje, and John Venable. 2011. “A Risk Management Framework for Design Science Research.” *Proceedings of the Annual Hawaii International Conference on System Sciences* 26 (1). https://doi.org/10.1109/HICSS.2011.27.

Bayer, Michael, Anders Haug, and Lars Hvam. 2020. “Differential Effects of Information Technology on Competitive Positioning.” *Industrial Management and Data Systems* 120 (10): 1923–39. https://doi.org/10.1108/IMDS-01-2020-0037.

Beer, David. 2018. “Envisioning the Power of Data Analytics.” *Information Communication and Society* 21 (3). Taylor & Francis: 465–79. https://doi.org/10.1080/1369118X.2017.1289232.

Benner, Mary J., and Michael L. Teshman. 2003. “Exploitation, Exploration, and

Process Management: The Productivity Dilemma Revisited.” *Academy of Management Review* 28 (2): 238–56.

Berinato, Scott. 2019. “Data Science & the Art of Persuasion.” *Harvard Business Review*, no. February: 126–38.

Bhaskar, R. 1978. *A Realist Theory of Science*. Hassock: Harvester Press.

Boer, Harry, Matthias Holweg, Martin Kilduff, Mark Pagell, Roger Schmenner, and Chris Voss. 2015. “Making a Meaningful Contribution to Theory Article Information: To Cite This Document.”

Bose, Ranjit. 2009. “Advanced Analytics: Opportunities and Challenges.” *Industrial Management & Data Systems* 109 (2): 155–72. https://doi.org/10.1108/02635570910930073.

Breiman, Leo. 2001. “Statistical Modeling: The Two Cultures.” *Statistical Science* 16 (3): 199–215. https://doi.org/10.1214/ss/1009213726.

Brinch, Morten. 2018. “Understanding the Value of Big Data in Supply Chain Management and Its Business Processes.” *International Journal of Operations and Production Management* 38 (7). https://doi.org/http://dx.doi.org/10.1108/MRR-09-2015-0216.

Brinch, Morten, Jan Stentoft, Jesper Kronborg Jensen, and Christopher Rajkumar. 2018. “Practitioners Understanding of Big Data and Its Applications in Supply Chain Management.” *The International Journal of Logistics Management* 29 (2): 555–74. https://doi.org/10.1108/IJLM-05-2017-0115.

Burgess, Kevin, Prakash J. Singh, and Rana Koroglu. 2006. “Supply Chain Management: A Structured Literature Review and Implications for Future Research.” *International Journal of Operations and Production Management* 26 (7): 703–29. https://doi.org/10.1108/01443570610672202.

Carillo, Kevin Daniel André. 2017. “Let’s Stop Trying to Be ‘Sexy’ – Preparing Managers for the (Big) Data-Driven Business Era.” *Business Process Management Journal* 23 (3): 598–622. https://doi.org/10.1108/BPMJ-09-2016-0188.

Chae, Bongsug, Chenlung Yang, David Olson, and Chwen Sheu. 2014. “The Impact of Advanced Analytics and Data Accuracy on Operational Performance: A Contingent Resource Based Theory (RBT) Perspective.” *Decision Support Systems* 59 (1). Elsevier B.V.: 119–26. https://doi.org/10.1016/j.dss.2013.10.012.

Chen, Daniel Q., David S. Preston, and Morgan Swink. 2015. "How the Use of Big Data Analytics Affects Value Creation in Supply Chain Management." *Journal of Management Information Systems* 32 (4). Routledge: 4–39. https://doi.org/10.1080/07421222.2015.1138364.

Chen, Injazz J., and Antony Paulraj. 2004. "Towards a Theory of Supply Chain Management: The Constructs and Measurements." *Journal of Operations Management* 22 (2): 119–50. https://doi.org/10.1016/j.jom.2003.12.007.

Chen, Philip C.L., and Chun-Yang Zhang. 2014. "Data-Intensive Applications, Challenges, Techniques and Technologies: A Survey on Big Data." *Information Sciences* 275 (August). Elsevier: 314–47. https://doi.org/10.1016/J.INS.2014.01.015.

Chira, R. 2002. *The Production of Management Knowledge: Philosophical Underpinnings of Research Design*. London: Sage.

Christensen, C.M., and M.E Raynor. 2003. "Why Hard-Nosed Executives Should Care about Management Theory." *Harvard Business Review* 81 (9): 1–10.

Chybalski, F. 2017. "Forecast Value Added (FVA) Analysis as a Means to Improve the Efficiency of a Forecasting Process." *Operations Research and Decisions* 27 (1): 5–19. https://doi.org/10.5277/ord170101.

Cooper, Martha C., Douglas M. Lambert, and Janus D. Pagh. 1997. "Supply Chain Management: More Than a New Name for Logistics." *The International Journal of Logistics Management*. https://doi.org/10.1108/09574099710805556.

Corbett, Charles, and Luk Van Wassenhove. 1993. "Trade-Offs? What Trade-Offs? Competence and Competitiveness in Manufacturing Strategy." *California Management Review* 35 (4).

Cottyn, J., H. Van Landeghem, K. Stockman, and S. Derammelaere. 2011. "A Method to Align a Manufacturing Execution System with Lean Objectives." *International Journal of Production Research* 49 (14): 4397–4413. https://doi.org/10.1080/00207543.2010.548409.

Coughlan, Paul, Domien Draaijer, Janet Godsell, and Harry Boer. 2016. "Operations and Supply Chain Management: The Role of Academics and Practitioners in the Development of Research and Practice." *International Journal of Operations and Production Management* 36 (12): 1673–95. https://doi.org/10.1108/IJOPM-11-2015-0721.

Croom, Simon, Pietro Romano, and Mihalis Giannakis. 2000. “Supply Chain Management: An Analytical Framework for Critical Literature Review.” *European Journal of Purchasing & Supply Management* 6 (1): 67–83. https://doi.org/10.1016/S0969-7012(99)00030-1.

Cupek, Rafal, Adam Ziebinski, Marek Drewniak, and Marcin Fojcik. 2018. “Knowledge Integration via the Fusion of the Data Models Used in Automotive Production Systems.” *Enterprise Information Systems* 13 (7–8). Taylor & Francis: 1094–1119. https://doi.org/10.1080/17517575.2018.1489563.

Davenport, Thomas H. 1993. *Process Innovation: Reengineering Work through Information Technology.* Boston: Harvard Business School Press.

Davenport, Thomas H. 2018. *The AI Advantage*. MIT Press Books.

Davenport, Thomas, and Jeanne G. Harris. 2007. *Competing on Analytics: The New Science of Winning*. Boston: Harvard Business School Press.

Davenport, Thomas, and Jeanne G. Harris. 2017. *Competing on Analytics*. Harvard Business Review Press.

Davis, Tom. 1993. “Effective Supply Chain Management.” *Sloan Management Review* 34 (4): 35. https://doi.org/10.1108/sd-04-2020-0081.

Delen, Dursun, and Hamed M. Zolbanin. 2018. “The Analytics Paradigm in Business Research.” *Journal of Business Research* 90 (May). Elsevier: 186–95. https://doi.org/10.1016/j.jbusres.2018.05.013.

Deloitte. 2019. “Democratizing Data Science in Your Organization.” https://hbr.org/sponsored/2019/04/democratizing-data-science-in-your-organization.

Deming, W.E. 1986. *Out of the Crisis*. Cambridge, MA: Massachusetts Institute of Technology.

Douglas, Lambert M., and C. Martha Cooper. 2000. “Issues in Supply Chain Management.” *Industrial Marketing Management* 29: 65–83.

Drechsler, Andreas, and Alan Hevner. 2006. “A Four-Cycle Model of IS Design Science Research: Capturing the Dynamic Nature of IS Artifact Design.” *University College Cork, Ireland*, 1–8.

Ellram, Lisa M., and Martha C. Cooper. 1990. “Supply Chain Management, Partnerships, And the Shipper -Third Party Relationship.” *The International Journal of Logistics Management*. https://doi.org/10.1108/95740939080001276.

Ellram, Lisa M., and Martha C. Cooper. 2014. “Supply Chain Management: It’s All about the Journey, Not the Destination.” *Journal of Supply Chain Management* 50 (1): 8–20. https://doi.org/10.1111/jscm.12043.

Eriksson, Carina Ihlström, Maria Åkesson, and Karlheinz Kautz. 2011. “Authentic and Concurrent Evaluation - Refining an Evaluation Approach in Design Science Research.” *PACIS 2011 - 15th Pacific Asia Conference on Information Systems: Quality Research in Pacific* (January).

Ernst, Alexander, and Alexander Schneider. 2010. “Roadmaps for Enterprise Architecture Evolution.” In *Workshop, Workshop on Patterns in Enterprise Architecture Management (PEAM 2010)*, 253–66. Paderborn, Germany.

Fosso Wamba, Samuel, Shahriar Akter, and Conference Paper. 2015. “Big Data Analytics for Supply Chain Management: A Literature Review and Research Agenda,” (June). Springer, Cham: 61–72. https://doi.org/10.1007/978-3-319-24626-0.

Fowler, Martin. 2019. “How to Move Beyond a Monolithic Data Lake to a Distributed Data Mesh.”

Gandomi, Amir, and Murtaza Haider. 2015. “Beyond the Hype: Big Data Concepts, Methods, and Analytics.” *International Journal of Information Management* 35 (2). Pergamon: 137–44. https://doi.org/10.1016/J.IJINFOMGT.2014.10.007.

Gartner. 2012a. “Magic Quadrant for BI Platforms. Analytics Value Escalator.”

Gartner. 2012b. “Pace-Layered Application Strategy.” https://www.gartner.com/en/information-technology/glossary/pace-layered-application-strategy#:~:text=Gartner’s Pace-Layered Application Strategy,business change%2C differentiation and innovation.

Ghasemaghaei, Maryam, Khaled Hassanein, and Ofir Turel. 2017. “Increasing Firm Agility through the Use of Data Analytics: The Role of Fit.” *Decision Support Systems* 101 (September). North-Holland: 95–105. https://doi.org/10.1016/J.DSS.2017.06.004.

Göbel, Hannes, and Stefan Cronholm. 2016. “Nascent Design Principles Enabling Digital Service Platforms.” *Lecture Notes in Computer Science (Including*

Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics) 9661: 52–67. https://doi.org/10.1007/978-3-319-39294-3_4.

Gregor, Shirley, Leona Chandra Kruse, and Stefan Seidel. 2020. “Research Perspectives: The Anatomy of a Design Principle.” *Journal of the Association for Information Systems* 21 (6): 1622–52. https://doi.org/10.17705/1jais.00649.

Gregor, Shirley, and Alan R Hevner. 2013. “Positioning and Presenting Design Science Research for Maximum Impact.” *MIS Quarterly* 37 (2): 337–55. https://doi.org/10.2753/MIS0742-1222240302.

Gunasekaran, A., and E.W.T. Ngai. 2004. “Information Systems in Supply Chain Integration and Management.” *European Journal of Operational Research* 159 (2 SPEC. ISS.): 269–95. https://doi.org/10.1016/j.ejor.2003.08.016.

Hahn, G.J., and J. Packowski. 2015. “A Perspective on Applications of In-Memory Analytics in Supply Chain Management.” *Decision Support Systems* 76 (August). North-Holland: 45–52. https://doi.org/10.1016/J.DSS.2015.01.003.

Halldórsson, A., J. Hsuan, and H. Kotzab. 2015. “Complementary Theories to Supply Chain Management Revisited – from Borrowing Theories to Theorizing.” *Supply Chain Management: An International Journal* 20 (6): 574–86.

Hayes, R., and S.C. Wheelwright. 1984. *Restoring Our Competitive Edge: Competing Through Manufacturing*. New York: John Wiley.

Hazen, Benjamin T., Christopher A. Boone, Jeremy D. Ezell, and L. Allison Jones-Farmer. 2014. “Data Quality for Data Science, Predictive Analytics, and Big Data in Supply Chain Management: An Introduction to the Problem and Suggestions for Research and Applications.” *International Journal of Production Economics* 154 (August). Elsevier: 72–80. https://doi.org/10.1016/j.ijpe.2014.04.018.

Herden, Tino T. 2017. “Similarity-Matching in Decision-Making Processes of Supply Chain Analytics: A Systematic Literature Review.” *Supply Chain Forum* 18 (1). Taylor & Francis: 13–20. https://doi.org/10.1080/16258312.2017.1278670.

Herden, Tino T. 2019. “Explaining the Competitive Advantage Generated from Analytics with the Knowledge-Based View: The Example of Logistics and Supply Chain.” *Business Research*. Springer International Publishing. https://doi.org/10.1007/s40685-019-00104-x.

Hevner, Alan. R. 2007. “A Three Cycle View of Design Science Research.”

Scandinavian Journal of Information Systems 19 (2): 87–92. https://doi.org/http://aisel.aisnet.org/sjis/vol19/iss2/4.

Hevner, Alan, Salvatore March, and Jinsoo Park. 2004. "Design Science in Information Systems Research." *MIS Quarterly: Management Information Systems* 28 (1).

Hevner, Alan, Salvatore March, Jinsoo Park, Sudha Ram. 2004. "Design Science in Information Systems Research." *MIS Quarterly: Management Information Systems* 28 (1): 75. https://doi.org/10.2307/25148625.

Holmström, J, M Ketokivi, and Ap Hameri. 2009. "Bridging Practice and Theory: A Design Science Approach." *Decision Sciences* 40 (1): 65–88. https://doi.org/https://doi.org/10.1111/j.1540-5915.2008.00221.x.

Holsapple, Clyde, Anita Lee-Post, and Ram Pakath. 2014. "A Unified Foundation for Business Analytics." *Decision Support Systems* 64: 130–41. https://doi.org/10.1016/j.dss.2014.05.013.

Holsapple, Clyde W., and Mark P. Sena. 2001. "Beyond Transactions: The Decision Support Benefits of ERP Systems." *Journal of Decision Systems* 10 (1): 65–85. https://doi.org/10.3166/jds.10.65-85.

Hult, G., Tomas M., Stanley F. Slater, and David J. Ketchen. 2004. "Information Processing, Knowledge Development, and Strategic Supply Chain Performance." *The Academy of Management Journal* 47 (2): 241–53. https://doi.org/10.1016/S0890-6955(97)00137-5.

Hurbean, L., and F. Doina. 2014. "ERP III The Promise of a New Generation." In *13th International Conference on Informatics in Economy, Education, Research & Business Technologies*. ASE Bucharest. https://doi.org/2247-1480.

Ishaya, Tanko, and Musiliudeen Folarin. 2012. "A Service Oriented Approach to Business Intelligence in Telecoms Industry." *Telematics and Informatics* 29 (3). Elsevier Ltd: 273–85. https://doi.org/10.1016/j.tele.2012.01.004.

Ivert, Linea Kjellsdotter. 2012. "Use of Advanced Planning and Scheduling (APS) Systems to Support Manufacturing Planning and Control Processes." Chalmers University of Technology.

Ivert, Linea Kjellsdotter, and Patrik Jonsson. 2011. "Problems in the Onward and Upward Phase of APS System Implementation: Why Do They Occur?" *International Journal of Physical Distribution & Logistics Management* 41 (4): 343–63. https://doi.org/http://dx.doi.org/10.1108/MRR-09-2015-0216.

Jacobs, F.R., W.L. Berry, D.C. Whyback, and T.E. Vollmann. 2011. *Manufacturing Planning and Control for Supply Chain Management*. McGraw-Hill Education.

Jeon, Byeong Woo, Jumyung Um, Soo Cheol Yoon, and Suh Suk-Hwan. 2017. "An Architecture Design for Smart Manufacturing Execution System." *Computer-Aided Design and Applications* 14 (4): 472–85. https://doi.org/10.1080/16864360.2016.1257189.

Jiang, P. Y., G. H. Zhou, G. Zhao, Y. F. Zhang, and H. B. Sun. 2007. "E2-MES: An e-Service-Driven Networked Manufacturing Platform for Extended Enterprises." *International Journal of Computer Integrated Manufacturing* 20 (2–3): 127–42. https://doi.org/10.1080/09511920601020664.

Jonsson, Patrik, and Jan Holmström. 2016. "Future of Supply Chain Planning: Closing the Gaps between Practice and Promise." *International Journal of Physical Distribution & Logistics Management* 46 (1): 62–81.

Jonsson, Patrik, and Linea Kjellsdotter Ivert. 2015. "Improving Performance with Sophisticated Master Production Scheduling." *International Journal of Production Economics* 168. Elsevier: 118–30. https://doi.org/10.1016/j.ijpe.2015.06.012.

Jüttner, Uta, Martin Christopher, and Janet Godsell. 2010. "A Strategic Framework for Integrating Marketing and Supply Chain Strategies." *International Journal of Logistics Management* 21 (1): 104–26. https://doi.org/10.1108/09574091011042205.

Kache, Florian, and Stefan Seuring. 2017. "Challenges and Opportunities of Digital Information at the Intersection of Big Data Analytics and Supply Chain Management." *International Journal of Operations & Production Management*. https://doi.org/10.1108/EMJB-06-2013-0034.

Khayer, Abul, Yukun Bao, and Bang Nguyen. 2020. "Understanding Cloud Computing Success and Its Impact on Firm Performance: An Integrated Approach." *Industrial Management and Data Systems* 120 (5): 963–85. https://doi.org/10.1108/IMDS-06-2019-0327.

Kim, Eunjin, and Byungtae Lee. 2009. "Strategic Use of Analytical CRM in a Market with Network Effects and Switching Costs: Terminating Unprofitable Customer Relationships." *Journal of Organizational Computing and Electronic Commerce* 19 (3): 153–72. https://doi.org/10.1080/10919390903041832.

Kiron, David, Pamela Kirk Prentice, and Renee Boucher Ferguson. 2014. "The Analytics Mandate." *MIT Sloan Management Review* 55 (4): 1.

Kiron, David, Rebecca Shockley, Nina Kruschwitz, Glenn Finch, and Michael Haydock. 2011. “Analytics: The Widening Divide Advantage through Analytics.” *MITSloan Management Review*, 1–21.

Kleppmann, Martin. 2017. *Designing Data-Intensive Applications*. O´Reilly Media.

Kridel, Don, and Daniel Dolk. 2013. “Automated Self-Service Modeling: Predictive Analytics as a Service.” *Information Systems and E-Business Management* 11 (1): 119–40. https://doi.org/10.1007/s10257-011-0185-1.

Lai, Yuanyuan, Huifen Sun, and Jifan Ren. 2018. “Understanding the Determinants of Big Data Analytics (BDA) Adoption in Logistics and Supply Chain Management: An Empirical Investigation.” *International Journal of Logistics Manpower* 29 (2): 676–703. https://doi.org/10.1108/IJLM-06-2017-0153 1.

Lambert, Douglas M., and Renan Burduroglu. 2000. “Measuring and Selling the Value of Logistics.” *The International Journal of Logistics Management* 11 (1): 1–18. https://doi.org/10.1108/09574090010806038.

Larson, Deanne, and Victor Chang. 2016. “A Review and Future Direction of Agile, Business Intelligence, Analytics and Data Science.” *International Journal of Information Management* 36 (5). Elsevier Ltd: 700–710. https://doi.org/10.1016/j.ijinfomgt.2016.04.013.

Lavalle, Steve, Eric Lesser, Rebecca Shockley, Michael S Hopkins, and Nina Kruschwitz. 2011. “Big Data, Analytics and the Path from Insights to Value.” *MIT Sloan Management Review* 52 (2): 21–32. https://doi.org/10.0000/PMID57750728.

Leventhal, Barry. 2015. “All Models Are Wrong but Some Are Useful: The Use of Predictive Analytics in Direct Marketing.” *Quality Technology and Quantitative Management* 12 (1): 93–104. https://doi.org/10.1080/16843703.2015.11673369.

Levinthal, Daniel A. 1991. “Organizational Adaptation and Environmental Selection-Interrelated Processes of Change.” *Organization Science* 2 (1): 140–45.

Levinthal, Daniel A, and James G March. 1993. “The Myopia of Learning” 14: 95–112.

Liberatore, Matthew J, and Wenhong Luo. 2010. “The Analytics Movement: Implication Operations Research.” *Interfaces Informs* 40 (4): 313–24.

Ling, R.C., and W.E. Goddard. 1988. *Orchestrating Success: Improve Control of the*

Business with Sales and Operations Planning. New York: John Wiley & Sons.

Lummus, Rhonda R., and Robert J. Vokurka. 2000. "Defining Supply Chain Management: A Historical Perspective and Practical Guidelines." *Value in Health* 3 (1): 11–17.

Mansour, Ikbal, Pierre Alain Millet, and Valérie Botta-Genoulaz. 2018. "A Standard-Based Business Repository for on-Demand Manufacturing Execution Systems." *Production Planning and Control* 29 (7). Taylor & Francis: 602–13. https://doi.org/10.1080/09537287.2018.1456691.

Marchand, Donald A, and Joe Peppard. 2013. "Why IT Fumbles Analytics." *Harvard Business Review*, no. 91: 104–12.

Martin, Christopher, and Ryals Lynette. 1999. "Supply Chain Strategy: Its Impact on Shareholder Value." *International Journal of Logistics Management* 10 (1): 1–18.

McAfee, Andrew, and Erik Brynjolfsson. 2012. "Big Data: The Management Revolution." *Harvard Business Review* 90 (10): 61–67. https://doi.org/00475394.

Mentzer, John T., Theodore P. Stank, and Terry L. Esper. 2008. "Supply Chain Management and Its Relationship to Logistics, Marketing, Production, and Operations Management." *Journal of Business Logistics* 29 (1): 31–46. https://doi.org/10.1002/j.2158-1592.2008.tb00067.x.

Mentzer, John T., William DeWitt, James S. Keebler, Soonhong Min, Nancy W. Nix, Carlo D. Smith, and Zach G. Zacharia. 2001. "Defining Supply Chain Management." *Journal of Business Logistics* 22 (2): 1–25. https://doi.org/10.1002/j.2158-1592.2001.tb00001.x.

Microsoft. 2021. "Team Data Science Process." Accessed January 6, 2021. https://docs.microsoft.com/en-us/azure/machine-learning/team-data-science-process/overview.

Miller, Jeffrey G., and Aleda V. Roth. 1994. "A Taxonomy of Manufacturing Strategies." *Management Science* 40 (3): 285–304.

Møller, Charles. 2005. "ERP II: A Conceptual Framework for Next-Generation Enterprise Systems?" *Journal of Enterprise Information Management* 18 (4): 483–97. https://doi.org/10.1108/17410390510609626.

Morais, Rinaldo Macedo de, Samir Kazan, Silvia Ines Dallavalle de Pádua, and André

Lucirton Costa. 2014. “An Analysis of BPM Lifecycles: From a Literature Review to a Framework Proposal.” *Business Process Management Journal* 20 (3): 412–32. https://doi.org/10.1108/BPMJ-03-2013-0035.

Neumeier, Anna, Thomas Wolf, Gilbert Fridgen, Hanna Vera Müller, and Carina Reith. 2017. “Natural and Design Science Perspective on the Business Value of It.” *AMCIS 2017 - America’s Conference on Information Systems: A Tradition of Innovation* 2017-August.

Nguyen, Truong, Li Zhou, Virginia Spiegler, Petros Ieromonachou, and Yong Lin. 2017. “Big Data Analytics in Supply Chain Management: A State-of-the-Art Literature Review.” *Computers and Operations Research*. Elsevier Ltd: 1–11. https://doi.org/10.1016/j.cor.2017.07.004.

Nicolai, Alexander, and David Seidl. 2010. “That’s Relevant! Different Forms of Practical Relevance in Management Science.” *Organization Studies* 31 (9–10): 1257–85. https://doi.org/10.1177/0170840610374401.

Norvig, Peter. 2009. “All We Want Are the Facts, Ma’am.” http://norvig.com/fact-check.html.

Oliver, R. Keith, and Michael D. Webber. 1982. "Supply-Chain Management: Logistics Catches up with Strategy." In *Logistics: The Strategic Issues*, edited by M.L. Christopher. London: Chapman & Hall.

Oztekin, Asil, Giles Hindle, Martin Kunc, Michael Mortensen, and Richard Vidgen. 2016. “Business Analytics: Defining the Field and Identifying a Research Agenda - Call for Papers - Elsevier.” *European Journal of Operational Research*. Elsevier B.V. https://doi.org/10.1016/j.ejor.2019.10.001.

Peffers, Ken, Tuure Tuunanen, Marcus A. Rothenberger, and Samir Chatterjee. 2007. “A Design Science Research Methodology for Information Systems Research.” *Journal of Management Information Systems* 24 (3): 45–77. https://doi.org/10.2753/MIS0742-1222240302.

Porter, Michael E., and Victor E. Millar. 1985. “How Information Gives You Competitive Advanage.” *Harvard Business Review* 63 (4): 149–60.

Porter, Michael E. 1985. “Technology and Competitive Advantage.” *Journal of Business Strategy* 130 (2): 556. http://dx.doi.org/10.1016/j.jaci.2012.05.050.

Prat, Nicolas, Isabelle Comyn-Wattiau, and Jacky Akoka. 2015. “A Taxonomy of Evaluation Methods for Information Systems Artifacts.” *Journal of Management Information Systems* 32 (3): 229–67.

https://doi.org/10.1080/07421222.2015.1099390.

Pries-Heje, Jan, Richard Baskerville, and John R. Venable. 2008. “Strategies for Design Science Research Evaluation.” In *European Conference on Information Systems*. Vol. 87.

Provost, Foster, and Tom Fawcett. 2013. “Data Science and Its Relationship to Big Data and Data-Driven Decision Making.” *Big Data* 1 (1): 51–59. https://doi.org/10.1089/big.2013.1508.

Quinton, Sarah. 2013. “The Digital Era Requires New Knowledge to Develop Relevant CRM Strategy: A Cry for Adopting Social Media Research Methods to Elicit This New Knowledge.” *Journal of Strategic Marketing* 21 (5): 402–12. https://doi.org/10.1080/0965254X.2013.801611.

Raisch, Sebastian, and Julian Birkinshaw. 2008. “Organizational Ambidexterity: Antecedents, Outcomes, and Moderators.” *Journal of Management* 34 (3): 375–409. https://doi.org/10.1177/0149206308316058.

Ramanathan, Ramakrishnan, Elly Philpott, Yanqing Duan, and Guangming Cao. 2017. “Adoption of Business Analytics and Impact on Performance: A Qualitative Study in Retail.” *Production Planning and Control* 28 (11–12). Taylor & Francis: 985–98. https://doi.org/10.1080/09537287.2017.1336800.

Rashid, Mohammad A, Liaquat Hossain, and Jon David Patrick. 2002. “The Evolution of ERP Systems: A Historical Perspective.” *Enterprise Resource Planning: Global Opportunities and Challenges*, 1–16.

Rockart, J.F. 1979. “Chief Executives Define Their Own Data Needs.” *Harvard Business Review* 57 (2): 81–93.

Romero, David, and François Vernadat. 2016. “Enterprise Information Systems State of the Art: Past, Present and Future Trends.” *Computers in Industry* 79 (March): 3–13. https://doi.org/10.1016/j.compind.2016.03.001.

Ross, W. Jeanne, M. Cynthia Beath, and Anne Quaadrgrass. 2013. “You May Not Need Big Data After All.” *Harvard Business Review* (December): 90–98.

Rudberg, Martin, and Jan Olhager. 2003. “Manufacturing Networks and Supply Chains: An Operations Strategy Perspective.” *Omega* 31 (1): 29–39. https://doi.org/10.1016/S0305-0483(02)00063-4.

Saberi, Morteza, Omar Khadeer Hussain, and Elizabeth Chang. 2017. “Past, Present and Future of Contact Centers: A Literature Review.” *Business Process*

Management Journal 23 (3): 574–97. https://doi.org/http://dx.doi.org/10.1108/MRR-09-2015-0216.

Sanders, Nada R. 2016. “How to Use Big Data to Drive Your Supply Chain.” *California Management Review* 58 (3): 26–48. https://doi.org/10.1525/cmr.2016.58.3.26.

Schoenherr, Tobias, and Cheri Speier-Pero. 2015. “Data Science, Predictive Analytics, and Big Data in Supply Chain Management: Current State and Future Potential.” *Journal of Business Logistics* 36 (1): 120–32. https://doi.org/10.1111/jbl.12082.

Sculley, D., Gary Holt, Daniel Golovin, Eugene Davydov, Todd Phillips, Dietmar Ebner, Vinay Chaudhary, Michael Young, Jean François Crespo, and Dan Dennison. 2015. “Hidden Technical Debt in Machine Learning Systems.” *Advances in Neural Information Processing Systems* 2015 (January): 2503–11.

Seddon, Peter B., Cheryl Calvert, and Song Yang. 2010. “A Multi-Project Model of Key Factors Affecting Organizational Benefits from Enterprise Systems.” *MIS Quarterly* 34 (2): 305–28.

Sein, K Maung, Ola Henfridsson, Sandeep Purao, Matti Rossi, and Rikard Lindgren. 2011. “Action Design Research.” *MIS Quarterly* 35 (1): 37–56.

Shearer, Colin. 2000. “The CRISP-DM Model: The New Blueprint for Data Mining.” *Journal of Data Warehousing* 5 (4): 23.

Silver, Edward A., David F. Pyke, and Rein Peterson. 1998. *Inventory Management and Production Planning and Scheduling*. Wiley.

Simon, H.A. 1996. *The Sciences of the Artificial*, 3rd ed. Cambridge, MA: MIT Press.

Skinner, W. 1969. “Manufacturing-Missing Link in Corporate Strategy.” *Harvard Business Review* (May–June): 136–45.

Sousa, Rui, and Christopher A. Voss. 2008. “Contingency Research in Operations Management Practices.” *Journal of Operations Management* 26 (6): 697–713. https://doi.org/10.1016/j.jom.2008.06.001.

Souza, Gilvan C. 2014. “Supply Chain Analytics.” *Business Horizons* 57 (5): 595–605. https://doi.org/10.1016/j.bushor.2014.06.004.

Stewart, Gordon. 1997. “Supply-Chain Operations Reference Model (SCOR): The First Cross-Industry Framework for Integrated Supply-Chain Management.”

Logistics Information Management 10 (2): 62–67.

Subramaniyan, Mukund, Anders Skoogh, Hans Salomonsson, Pramod Bangalore, and Jon Bokrantz. 2018. “A Data-Driven Algorithm to Predict Throughput Bottlenecks in a Production System Based on Active Periods of the Machines.” *Computers and Industrial Engineering* 125 (April). Elsevier: 533–44. https://doi.org/10.1016/j.cie.2018.04.024.

Taylor, F.W. 1911. *The Principles of Scientific Management*. New York: Harper & Brothers.

Thieullent, Anne-Laure, Mathieu Colas, Buvat Jerome, Subrahmanyam K.V.J., and Bisht Ashish. 2016. “Going Big: Why Companies Need to Focus on Operational Analytics Operational Analytics : A Strategic Priority That Remains Unexploited.” Paris: Capgemini.

Toffel, Michael W. 2016. “Enhancing the Practical Relevance of Research.” *Production and Operations Management* 25 (9): 1493–1505. https://doi.org/10.1111/poms.12558.

Trkman, Peter, Kevin Mccormack, Marcos Paulo Valadares de Oliveira, Marcelo Bronzo Ladeira, Marcos Paulo Valadares de Oliveira, and Marcelo Bronzo Ladeira. 2010. “The Impact of Business Analytics on Supply Chain Performance.” *Decision Support Systems* 49 (3). Elsevier Science Publishers B. V.: 318–27. https://doi.org/10.1016/j.dss.2010.03.007.

Ugarte, B. Saenz De, A. Artiba, and R. Pellerin. 2009. “Manufacturing Execution System - A Literature Review.” *Production Planning and Control* 20 (6): 525–39. https://doi.org/10.1080/09537280902938613.

van Aken, J.E. 2004. “Management Research on the Basis of the Design Paradigm: The Quest for Field-Tested and Grounded Technological Rules.” *Journal of Management Studies* 41 (2): 219–46. https://doi.org/0022-2380.

Vanauer, Martin, Carsten Bohle, and Bernd Hellingrath. 2015. “Guiding the Introduction of Big Data in Organizations: A Methodology with Business- and Data-Driven Ideation and Enterprise Architecture Management-Based Implementation.” In *2015 48th Hawaii International Conference on System Sciences*, 908–17. https://doi.org/10.1109/HICSS.2015.113.

Van de Ven, Andrew H. 2007. *Engaged Scholarship*. New York: Oxford University Press.

Venable, John, Jan Pries-Heje, and Richard Baskerville. 2016. “FEDS: A Framework for Evaluation in Design Science Research." *European Journal of Information Systems* 25 (1). Nature Publishing Group: 77–89. https://doi.org/10.1057/ejis.2014.36.

Viaene, Stijn, and Annabel Van Den Bunder. 2011. "The Secrets to Managing Business Analytics Projects." *MIT Sloan Management Review* 53 (1): 65–69.

Waller, Matthew A., and Stanley E. Fawcett. 2013. "Data Science, Predictive Analytics, and Big Data: A Revolution That Will Transform Supply Chain Design and Management." *Journal of Business Logistics* 34 (2): 77–84. https://doi.org/10.1111/jbl.12010.

Weihrauch, Dennis, Paul Anton Schindler, and Wilfried Sihn. 2018. "A Conceptual Model for Developing a Smart Process Control System." *Procedia CIRP* 67. Elsevier B.V.: 386–91. https://doi.org/10.1016/j.procir.2017.12.230.

Wiengarten, Frank, Paul Humphreys, Guangming Cao, and Marie Mchugh. 2013. "Exploring the Important Role of Organizational Factors in IT Business Value: Taking a Contingency Perspective on the Resource-Based View." *International Journal of Management Reviews* 15 (1): 30–46. https://doi.org/10.1111/j.1468-2370.2012.00332.x.

Wirth, Rüdiger. 2000. "CRISP-DM : Towards a Standard Process Model for Data Mining." *Proceedings of the Fourth International Conference on the Practical Application of Knowledge Discovery and Data Mining*, no. 24959: 29–39. https://doi.org/10.1.1.198.5133.

Wixom, Barbara H., Bruce Yen, and Michael Relich. 2013. "Maximizing Value from Business Analytics." *MIS Quarterly Executive* 12 (June): 111–23. https://doi.org/10.1108/02635570910926564.

Xing, Yiting, Ling Li, Zhuming Bi, Marzena Wilamowska-Korsak, and Li Zhang. 2013. "Operations Research (OR) in Service Industries: A Comprehensive Review." *Systems Research and Behavioral Science* 30: 300–353. https://doi.org/10.1002/sres.

Zhong, Ray Y., Chen Xu, Chao Chen, and George Q. Huang. 2017. "Big Data Analytics for Physical Internet-Based Intelligent Manufacturing Shop Floors." *International Journal of Production Research* 55 (9). Taylor & Francis: 2610–21. https://doi.org/10.1080/00207543.2015.1086037.

Zhong, Ray Y., Stephen T. Newman, George Q. Huang, and Shulin Lan. 2016. "Big Data for Supply Chain Management in the Service and Manufacturing Sectors: Challenges, Opportunities, and Future Perspectives." *Computers and*

Industrial Engineering 101 (November). Elsevier Ltd: 572–91. https://doi.org/10.1016/j.cie.2016.07.013.

Zhu, Kevin, and Kenneth L. Kraemer. 2005. “Post-Adoption Variations in Usage and Value of e-Business by Organizations: Cross-Country Evidence from the Retail Industry.” *Information Systems Research* 16 (1): 61–84. https://doi.org/10.1287/isre.1050.0045.

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