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BY
MARIA HOFFMANN JENSEN

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AALBORG UNIVERSITY
DENMARK

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PhD supervisor:	Professor Peter Axel Nielsen, Aalborg University
Assistant PhD supervisor:	Associate Prof. John S. Persson, Aalborg University
Company supervisors:	Kim Emil Andersen Sven Jesper Knudsen
PhD committee:	Associate Professor Dimitrios Raptis Aalborg University, Denmark Professor Patrick Mikalef Norwegian University of Science and Technology, Norway Associate Professor Jacob Nørbjerg Copenhagen Business School, Denmark
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ABOUT THE AUTHOR

Maria Hoffmann Jensen has conducted research within the information systems discipline since 2018, stemming from her interest in how data can benefit organizations, society, and individuals. Based on experience from previous positions in industry, she is driven by the desire to understand how to bridge big data analytics to the organization that wishes to deploy it and create evident benefits. She wishes to bring big data analytics and people closer together and not solely focus on the technologies necessary for it. Maria is thus driven by questions such as: How do we bridge the business demand for analytics to the technology needed and measure if it had any effect on the way we behave from data? How do we apply big data analytics in an organization? What benefits do big data analytics enable?

Maria approaches her research interest from previous industry experience working with analytics and from the joint affiliation as an industrial PhD between Aalborg University, Department of Computer Science and Vestas Wind Systems A/S. As an industrial researcher, Maria believes that the best solutions and interesting research result from researchers and practitioners working closely together.

Til mine forældre, søstre, og min lille familie Frank, Emil og Asger.

ENGLISH SUMMARY

In this dissertation, I investigate how to engineer a method for realizing benefits from big data analytics projects. These types of projects can be complex and of high risk. Particularly, there is a risk of not delivering the solutions expected by the organization. The inherent complexity requires cross-departmental collaboration, which involves different skills from those involved. Big data analytics projects involve various elements, such as delivering the needed technology to capture, analyze, evaluate, and deploy data. The intangible nature of what big data analytics projects essentially deliver, and how the organization expects to reap value from this adds to their complexity. Principally, big data analytics deliver an information statement in the form of, e.g., predictions or prescriptive analytics, to be consumed and acted upon in the organization, which might lead to value. Yet the latter depends upon several other factors, which I will present in this dissertation. The question of how big data analytics creates benefits has captured the attention of researchers within the field. While many advances have been made within the field in terms of technologies, few studies provide an in-depth analysis of how benefits are realized, i.e., how we bridge the gap from big data technology to benefit realization. This is a key challenge from big data analytics that I address in this dissertation guided by the main research question:

How can we engineer a method for creating benefits with big data analytics projects?

I address the main research question from two perspectives: boundaries and dependencies, drawing upon the research fields of benefits management and systems thinking concerning big data analytics benefits. The dissertation's contribution is a proposal of a method and lessons for creating benefits with big data analytics projects based on a system thinking perspective. I argue that a benefit focus begins at the project level, but benefits instead materialize post-project in their organizational use. Based on findings from five studies, I propose a tailored version of the benefits dependency network as a fit for big data analytics projects. Moreover, I present contributions to how big data analytics benefits become evident in addressing the boundaries and dependencies associated with these. To this, findings portray social roles, specific concerns and key problems in making a benefit evident. Finally, I address 1) the measurement of benefits, which presents lessons on how benefits require change and change requires measurement, 2) establishing measurement depending on the type of ´who` involved in benefits realization and 3) how explicit measurement is dependent upon other contextual measures as the first two lessons presented. This dissertation suggests several further research opportunities, including evaluating big data analytics benefits from a systemic perspective and validating the lessons on measurement in several big data analytics projects.

DANSK RESUME

I denne afhandling undersøger jeg, hvorledes man kan designe en metode for realisering af nytte fra big data analytics-projekter. Et sådant projekt er både kompleks og har en høj risiko for ikke at opnå de løsninger og den nytte, som en organisation forventer. Big data analytics-projekter kræver tværgående samarbejde imellem forskellige afdelinger, der kan involvere forskellige typer af aktører med specifikke kompetencer. Herudover består sådanne projekter af forskellige elementer såsom at udvikle og levere den nødvendige teknologi til at opsamle, analysere, evaluere og implementere løsningerne ud fra big data. Kompleksiteten forstærkes af det immaterielle produkt i form af information, som big data analytics-projekter leverer, samt hvorledes en organisation forventer at opnå nytte fra denne information. Big data analytics producerer information, som for eksempel kan være baseret på forudsigende eller præskriptiv analyse, som der så skal forstås og ageres ud fra i organisationen. Denne ageren leder eventuelt til nytte, men det er ikke givet. At opnå nytte fra big data analytics-projekter er afhængig af adskillige faktorer, som jeg diskuterer i denne afhandling. Spørgsmålet om, hvorledes big data analytics skaber nytte, har tiltrukket opmærksomhed fra forskellige forskere, men til trods for at big data samt big data analytics som et forskningsfelt har set mange gennembrud, består det stadig af få studier med en dybdegående analyse af, hvorledes nytte bliver realiseret. Hvordan man går fra at fokusere på selve teknologierne til i stedet realisering af nytte, er en essentiel udfordring, som jeg adresserer i denne afhandling. Dette gør jeg ud fra forskningsspørgsmålet: **Hvordan kan man designe en metode for at skabe nytte med big data analytics projekter?**

Forskningsspørgsmålet bliver besvaret ud fra to perspektiver, der omhandler afgrænsninger samt afhængigheder. Disse perspektiver udspringer fra forskningsfelterne benefits management samt systemtænkning, der sættes i relation til nytten af big data analytics. Afhandlingens bidrag er en metode samt læring for, hvorledes et big data analytics-projekt kan skabe nytte ved at forstå dette som et større system. Jeg diskuterer, hvorledes et fokus på nytte begynder på projektniveauet, men at nytten materialiseres, når projektet er afsluttet og bliver brugt i organisationen. På dette grundlag præsenterer jeg en modificeret version af benefits dependency network for big data analytics-projekter. Herudover præsenterer jeg bidrag til, hvorledes nytte fra big data analytics-projekter bliver indlysende ved at adressere deres forståelse af afgrænsning fra de aktører, som er involveret i denne ud fra sociale roller, specifikke samt interessent- bekymringer. Afslutningsvis præsenteres bidrag til at etablere måling for big data analytics nytte, hvortil denne skal etableres ud fra ændringer i praksis, hvem som er involveret i nytten, og at eksplicit måling, som i finansiel måling, er afhængig af andre sammenhænge. Afhandlingens bidrag leder til adskillige fremtidige forskningsmuligheder, såsom at validere bidragene i andre organisationer og undersøge i selve den organisatoriske forankring af nytten.

ACKNOWLEDGEMENTS

This journey began years back when I lived in Hamburg, Germany. I remember how the motivation and wondering concerning the topic and the question posed in this dissertation, began to emerge. It led to many long and late hours trying to write down my ideas and thoughts that hopefully, at some point, could lead to a research proposal. Having been away from academia for quite some years, this was not an easy task. On top of that, I also had to find both an organization willing to invest in my ideas and a university that would supervise. Well, who doesn't like a challenge? Several years (and frustrations) later I have now finally managed to do what I hoped and dreamed about I would be able to achieve. I have handed in my PhD dissertation including five different papers. You can almost hear the sigh of relief and stress slowly damping of the shoulders.

Despite being quite lonely at times, a PhD study and handing in the PhD dissertation is not a lonely achievement. Throughout the years there have been some very important people that I owe great gratitude for my achievements. First, I must thank Vestas for being open-minded and willing to invest in my ideas. I owe special thanks to my two company supervisors Kim Emil Andersen and Sven Jesper Knudsen that despite their very technical background in statistics, were open towards more socio-technical ideas in their work. Both of you have been instrumental in achieving the results in the papers presented. Thank you for believing in me. Second, I must thank Aalborg University, the department of Computer Science and especially my university supervisors Peter Axel Nielsen and John Stouby Persson. You taught me a tremendous amount of things throughout the years, and I thank you for your patience with me having to return to academia again. Third, I must thank my friends for caring and listening to me in times of frustrations, stress, but also joy and excitement about my PhD. I thank you for picking me up whenever I felt as the world's worst PhD student ever.

Finally, I cannot begin to explain my gratitude towards my family. My parents, Karin and Henrik, with their unconditional love and support despite not always understanding why my head was about to explode from writing. I thank you for always building up my confidence. My beautiful and clever sisters, Lena and Tina. Thank you for your endless love and reminding me what is important in life and who I am.

The last words of my acknowledgements are dedicated to my own little family that emerged during the time of my PhD. My children, Emil and Asger, who gave me the most important title of my life. I love you endlessly. To Frank, for your patience, critical questions, and your confidence in me. Your support and love have been invaluable.

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ABBREVIATIONS

IS/IT: Information System/Information Technology	SAIC: System Analysis and Intelligent Computing	ITI: Interaction, Transformation and Information Systems development
BDA: Big Data Analytics	DevOps: Development and Operations	PHC: Precision Health-Care
Vestas: Vestas Wind Systems A/S	SSM: Soft System Methodology	CSH: Critical System Heuristics
SCADA: Supervisory Control And Data Acquisition	RD: Root Definition	CPR: Collaborative Practice Research
CRISP-DM: Cross-Industry Standard Process for Data Mining	CATWOE: Customers, Actors, Transformation, World-view, Owner, Environment	AEP: Annual Energy Production
KDD: Knowledge Discovery in Databases	The three E's: Efficacy, Efficiency and Effectiveness	BRM: Benefits Realization Management
SEMMA: Sampling, Exploring, Modifying, Modeling, and Assessing large amounts of data.	DEA: Data Envelopment Analysis	BDN: Benefits Dependency Network

1. INTRODUCTION

An effective data-driven organization must organize itself flexibly to maximize cross-functional cooperation. With big data, expertise is not where it used to be, as information is now created and transferred more frequently. Big data is defined by high data volume, the high velocity of several data sources, a high variety of data, and veracious data (Goes, 2014). A critical aspect of big data is its utilization and impact on how decisions are made and whom in the organizations that makes decisions. A recent literature review found that researchers generally address big data from four different perspectives; (1) information, (2) technology, (3) methods, and (4) impact (De Mauro *et al.*, 2015). The latter two lead to important questions: how can big data be better utilized in an organization, and how can it create value? These very complex questions have started to capture the attention of big data researchers (Lavalle *et al.*, 2011; De Mauro *et al.*, 2015; Mikalef, Krogstie, *et al.*, 2020; Monino, 2021). While many advances have been made in big data research and data science, few academic studies have provided an in-depth analysis of how big data becomes value assets (Heidrich *et al.*, 2016), i.e., how we move from big data technologies to value realization and impact. This is the key challenge of big data analytics. Moving from solely focusing on the big data analytics technologies to also focusing on the big data analytics benefits provided to the organization and stakeholders as receivers of these.

This Ph.D. dissertation investigates how big data analytics can create both tangible and intangible benefits with a particular focus on the project level. The dissertation's focus is to develop a new method for creating benefits from big data analytics projects, inspired by benefits management known from IS/IT and systems thinking based on a thorough analysis of the challenges this type of project encounters in addressing benefits. In the following sections, I present different elements of big data analytics and its benefits. To understand this dissertation, it is important to have a conceptual understanding of these.

1.1. FROM BIG DATA TO BIG DATA ANALYTICS

The notion of big data analytics has been one of the most prominent buzzwords within IS research since its first introduction more than ten years ago (Constantiou and Kallinikos, 2015). In addition, many research areas outside of IS research have adopted it, ranging from supply chain performance, marketing, and healthcare (Mikalef *et al.,* 2020). But why have big data analytics become such a trend? Essentially, big data analytics hold enormous potential in realizing transactional, informational, transformational, and strategic value (Elia *et al.,* 2020). Some scholars argue that big data analytics and the insights it can generate are particularly relevant in volatile and dynamic business environments where there is a need to innovate continuously to stay competitive (Prescott, 2014; Müller *et al.,* 2018).

However, before digging any further into what big data analytics is and can do, it is imperative to clearly distinguish between big data, big data analytics and big data analytics capability. These concepts are often used interchangeably within the literature. However, they are essentially very different in their theoretical underpinnings regarding how they are perceived and measured (Cao *et al.*, 2015). Moreover, I will briefly present what big data analytics projects mean, as these have been the object of investigation in this PhD. So, for the sake of continuous clarity of this PhD dissertation, I will briefly go through each of these concepts and explain the focus of this PhD regarding big data analytics. We begin with big data.

The period from 2001 to 2008 was the evolutionary stage for big data (Wang *et al*., 2018). First, the concept of big data is typically described by using the notorious V's being Volume, Velocity and Variety (McAfee and Brynjolfsson, 2012). Volume is concerned with the amount of data available for organizations to analyze from the aggregation of a large number of variables and multiple observations (Gupta and George, 2016). Volume is also commonly expressed in petabytes or exabytes, making it difficult for conventional databases to handle (Akter *et al.*, 2016). Velocity is the speed at which data is generated, collected and analyzed (George *et al.,* 2016). Moreover, velocity is expressed by the rate at which it essentially becomes obsolete (George *et al.,* 2016). Some scholars argue that the newness of the data collected and the capacity to analyze the big data are important factors in gaining a competitive advantage by improving business agility and enabling real-time action (Boyd and Crawford, 2012). Finally, variety concerns the numerous structured and unstructured data sources to which big data can refer. For example, big data can include audio, images, text, networks, sensory data and graphics, to mention a few (Constantiou and Kallinikos, 2015; George *et al.,* 2016).

Over time, several scholars have tried to conceptualize big data further by adding more V's to its definition: veracity, value, variability and visualization (Mikalef *et al.*, 2017). First, veracity concerns the accuracy or truthfulness of the big data (Abbasi *et al.*, 2016). Truthfulness refers to whether the big data is trusted, authentic, and protected from modification or ungranted access. It is imperative for decision-making in business management (Akter *et al.*, 2016). The value aspect was also introduced at a late stage and essentially represents the extent to which big data generates economic value or other benefits through extraction and transformation (Wamba et al., 2015). Many studies have investigated why big data fails to deliver value, and big data is frequently described as having a low value density compared to the amount of data being processed (ORACLE, 2012). Finally, Seddon et al., (2017) introduced two additional aspects of big data: variability and visualization. Variability refers to how the meaning of the big data acquired is constantly changing and presents the potential dynamic opportunities available from the interpretation of big data. Visualization means interpreting the trends and patterns in the big data in meaningful ways, e.g., through machine learning, artificial intelligence, etc. that then leans more towards big data analytics (Seddon and Currie, 2017).

At the beginning of 2009, big data analytics entered the revolutionary stage (Bryant *et al.,* 2008). As a field, big data analytics is related to business intelligence & analytics in terms of data mining and statistical analysis (Chen, Chiang and Storey, 2012a). Côrte-real *et al.*, (2017) describe big data analytics as *"a new generation of technologies of architectures, designed to economically extract value from very large volumes of a wide variety of data, by enabling high velocity capture, discovery and/or analysis"* (p. 380). Essentially, big data analytics revolve around three main characteristics. First is the data itself. Second, the analytics applied to the data. And third is the presentation of the analytics results, aiming to generate business value (Gantz and Reinsel, 2012).

Big data analytics can produce both intangible and tangible benefits for an organization. It encompasses not only big data but also the elements of big data analytics tools, infrastructures, and ways to visualize the insights generated *(*Kwon *et al.,* 2014; Lamba and Dubey, 2015). Big data is then infused into what we may refer to as the big data analytics process in generating insights for an organization. Big data analytics can include unstructured data based on cloud technologies (Wang *et al.*, 2018). Organizations are increasingly investing in cloud solutions for big data analytics, such as software-as-a-service (SaaS), which offer an attractive alternative to in-house development and storage in terms of costs. However, becoming an organization driven by big data analytics is a complex and multifaceted task that goes beyond implementing the technologies necessary for big data analytics. It necessitates attention at various levels from the practitioners involved. Therefore, scholars have begun to look into the term big data analytics capability.

In broad terms, the notion of big data analytics capability may be described as an organization's ability to provide insights for decision-making using data management, infrastructure, and talent to gain a competitive advantage (Akter et al., 2016; Ransbotham *et al.,* 2016). Big data analytics capability refers to an organization's capability to adopt and leverage the analytical insights generated from big data analytics. Some definitions of big data analytics capabilities focus on the processes needed to gain advantages from big data (Cao *et al.,* 2015). Other definitions focus on the necessary resources and the alignment of these to the organization's strategy (Xu and Kim, 2014). Lavalle *et al.*, (2011) categorize big data analytics capabilities into three levels: aspirational, experienced, and transformed. Organizations at the aspirational level have very few of the necessary capabilities to leverage big data analytics in relation to people, processes, and tools. They often focus on efficiency or automatization of existing processes to cut costs. Organizations at the experienced level have gained some success from their aspirational phase and are thus looking beyond cost improvements. Organizations at this level are better at effectively incorporating and acting on big data analytics. Finally, organizations at the transformed level are very experienced and use big data analytics across many functions. For them, big data analytics is a competitive differentiator and is more focused on driving customer profitability and target investments in niche analytics to keep innovating. Yet, reaching the transformed level is not easy, and many organizations struggle to move past the aspirational (Lavalle *et al.*, 2011). There is limited empirical research in relation to the notion of big data analytics capability and how to build this (Mikalef *et al.,* 2017). Moreover there are divergent views about what a big data analytics capability constitutes as different theoretical lenses are often employed in assessing it. Most commonly these are the resource-based theory and dynamic capabilities view of the firm.

Finally, it is worthwhile to address what is meant by the notion of a big data analytics project. Most of us are familiar with projects, both in a corporate setting and maybe from our private life with, for example, "I'll do it my-self" projects (that we typically regret later). Despite the different settings, a project is a delimited task with a start and end point within a given timeframe. Commonly, the project has a set budget and resource allocation. According to the Project Management Institute, a project can be defined as a *"temporary effort to create value through a unique product, service or result (and that) all projects have a beginning and an end…a team, a budget, a schedule and a set of expectations the team needs to meet"* (PMI, 2022, p.1). This could, for example, be to build a new type of wind turbine, a bridge, or maybe a new fence facing your neighbor. The latter three examples all entail a tangible delivery at the end of the project. For big data analytics projects, this can be quite different. Tsoy & Staples (2021) modified Chen *et al.*, (2012)'s definition of Business Intelligence and Analytics to better fit big data analytics projects: *"An (BDA) Analytics Project relates to the development and/or use of techniques, technologies, systems, practices, methodologies, and applications that analyze critical business data to help an enterprise better understand its business and market and make timely decisions"*(p. 324).

Big data analytics projects can be complex and highly risky in delivering the expected solution. Moreover, these projects require departments to work across their defined boundaries, which then involves actors with various skills (Maritz *et al.,* 2020; Sfaxi and Ben Aissa, 2020; Mikalef and Gupta, 2021). A big data analytics project typically involves the succession of several stages: data collection, data cleaning, feature engineering, modeling, evaluation, and deployment (Japkowicz and Stefanowski, 2016). Yet, big data analytics projects tend to rely on methods better suited to another setting. These include 1) Business intelligence methods, 2) Data mining development principles or 3) Agile principles. For big data analytics projects, due to the type of data included, variety of tools and architectural demand, the aforementioned methods are difficult to apply to these type of projects (Sfaxi and Ben Aissa, 2020).

Organizations investing in big data analytics aim to achieve benefits using the aforementioned concepts. I have applied the terms big data analytics and big data analytics projects in this PhD dissertation.

1.2. BIG DATA ANALYTICS BENEFITS

Now that we have clarified some of the different concepts in big data analytics, we can begin to unfold what many organizations strive for with their big data analytics projects – namely, benefits from these. Therefore, this section will present the benefits, which some scholars refer to as value propositions and the challenges with these.

First, a benefit can be defined as *"an advantage on behalf of a particular stakeholder or group of stakeholders"* (Ward & Daniel, 2012, p. 70). Throughout my PhD, I have used the term benefit instead of, for example, value or value propositions. My usage is based on Ward & Daniel (2012)'s definition. They use the term "advantage," which can be both financial and non-financial. Using the term value tends to lead the discussion toward financial advantages. However, several studies indicate that big data analytics can foster both financial and non-financial benefits (vom Brocke *et al.,* 2014; Loebbecke and Picot, 2015; Sodenkamp *et al.,* 2015; Günther *et al.,* 2017; Mikalef *et al.,* 2020).

Benefits from big data analytics come in many forms. They are perceived as a source for innovating new products, services, and business opportunities. These all make it very attractive for organizations to invest in (Davenport *et al.*, 2012; McAfee and Brynjolfsson, 2012; Davenport and Kudyba, 2016; P. B. Seddon *et al.*, 2017). Using content analysis, (Wang *et al.,* 2018) derive five categories of big data analytics benefits: IT infrastructure benefits, operational benefits, organizational benefits, managerial benefits, and strategic benefits. More specific elements for each of these categories include: reducing system redundancy, improving the quality and accuracy of decisions (clinical), and transferring of data quickly among systems. Many studies report organizations seeking for value creating opportunities, for example: enhancing digital business strategies (Bharadwaj *et al.*, 2013), transformation of the supply chain (Wang *et al.,* 2016), increasing market share (Wamba *et al.,* 2017) and general improving organizational performance (Ji-fan Ren *et al.,* 2017). Elia *et al.*, (2020) conducted a literature review for big data value creation in the marketing domain. They presented a framework that outlines the multiple benefits directions that big data can potentially generate for the organizations investing in this. Along eleven distinct value directions, they group these in five dimensions: informational, transactional, transformational, strategic, and infrastructural value. In other words, several studies and practitioners acknowledge that big data analytics may potentially provide benefits for an organization investing in this. However, big data analytics also comes with several challenges concerning the technologies and the potential benefits (Erevelles *et al.*, 2016; Jensen *et al.,* 2019).

Papers studying big data analytics benefits and the adoption of the technologies relevant for this point to the importance that benefits from the big data analytics technologies do not materialize from the technical implementation alone (Chen *et al.*, 2012; Marchand and Peppard, 2013; Ransbotham *et al.,* 2016). In acknowledging this challenge, research efforts have moved from focusing on the technological issues to the benefits-oriented dimensions that represent the business expectations and the extended impact of big data analytics encompassing both technological, economic, and organizational challenges (Raguseo, 2018). Akter *et al.*, (2016) point to the more recent efforts in implementing big data analytics in organizations based on the entanglement of both management, technology, and different types of resources to achieve benefits, measure performance, and gain a competitive advantage (Fosso Wamba *et al.,* 2015).

As confirmed by an in-depth study by Günther *et al.*, (2017), adopting big data analytics in organizations does not always generate benefits. There is a gap between transforming the extracted insights from big data analytics into the organization and effectively supporting decision-making and generating benefits. According to Verma & Bhattacharyya (2017), organizations fail to realize the strategic value that big data analytics entails, together with the realization of the necessity that big data analytics requires changes pertaining to existing organizational practices in relation to technology, work practices, processes, capabilities etc. This view was supported in earlier studies by (Lavalle *et al.*, 2011; Barton *et al.,* 2012), and it is questionable why the challenges of realizing benefits from big data analytics still prevail despite years of research and studies. Yet, some scholars argue that big data analytics benefits research is scarce (Côrte-Real *et al.*, 2014) and ought to extend beyond post-adoption stages towards competitiveness (Erevelles *et al.*, 2016).

A central challenge for big data analytics benefits is that several organizations essentially do not completely understand how best to use and implement big data analytics to improve their performance. This is because big data analytics provide an information statement in the form of analytics to be consumed in a given setting before it can materialize as a benefit (Sharma *et al.* 2014; Abbasi *et al.,* 2016). Further, formulating and appraising benefits is a complex task as big data analytics benefits are often dynamic and mean different things to the various stakeholders involved (Chang *et al.,* 2013). This difficulty is often amplified in big data analytics projects where ambiguity and stakeholder management issues may be multifaceted and complex, and aligning the organization's different entities in these projects is challenging yet essential (Akter *et al.,* 2016; Larson and Chang, 2016; Wamba *et al.*, 2017; Ghasemaghaei *et al.,* 2018).

In short, while many advances have been made for big data analytics in relation to the technologies and types of analytics that can be applied in big data analytics, few academic studies have provided an in-depth analysis of how it becomes value assets (Lavalle *et al.*, 2011; Abbasi *et al.,* 2016; Mikalef *et al.,* 2017; Côrte-Real *et al.,* 2019). Moving from solely focusing on the big data analytics technologies to benefit realization and impact is a key challenge for big data analytics research, which was the aim and motivation for this PhD study. As an industrial PhD, this dissertation is the result of a collaboration between an organization investing significantly in big data analytics, Vestas Wind Systems A/S, and Aalborg University, Computer Science. Engaging with a specific organization throughout the PhD has allowed me to engage in in-depth studies of multiple big data analytics projects over time. Thus, before moving to the research question of this PhD dissertation, the following section will introduce Vestas Wind Systems A/S as an organization and why this organization was an appropriate case for investigating big data analytics benefits.

1.3. THE CASE OF VESTAS WIND SYSTEMS A/S

Vestas is a wind turbine manufacturer and service provider that, for more than 40 years, has driven the global energy transition towards renewables. Vestas is a global organization installing and servicing wind turbines in various countries employing more than 29,000 employees as of 2021. From 2021, the organization installs and services turbines on and offshore due to integrating what was formerly MHI Vestas. At the outset of Vestas' renewables journey, the impact of the turbines was limited. Today, as technology has developed in the form of bigger turbines and advanced analytics, a single turbine can power up to 20,000 domestic homes at a cost-competitive scale compared to conventional energy sources.

The magnitude of climate change has become apparent across several countries. When the Intergovernmental Panel on Climate Change released its sixth report in August 2021, UN Secretary-General António Guterres declared "code red for humanity," the need for competitive renewable energy sources became even more apparent. The urgency toward adopting renewable energy sources was further highlighted at COP26 in Glasgow on November 21. Here climate targets were increased, additional countries announced net zero targets, and the phase-out of coal was included for the first time. Essentially, the market outlook for renewable energy organizations like Vestas is positive. Yet competition among wind turbine manufacturers is high. In recent years, the industry has been dominated by several challenges. These include increasing raw materials costs, quality issues, supply chain waste, complex market structures, protectionism, and trade barriers. To address some of these challenges, Vestas has invested significantly in its analytics capabilities, providing the organization with a competitive advantage in overcoming some of the aforementioned challenges.

In 2013 Vestas purchased the world's third largest commercial supercomputer, "Firestorm," quickly followed by the purchase of the supercomputer "Mindstorm" in 2016. For example, Vestas has built a climate library with hour-by-hour data to predict and model the performance of potential wind farms. The climate library holds global data and includes more than 38.000 turbines online in the system providing data in real-time, historical data from more than 61.000 installed turbines as well as 10.000 meteorological masts. The climate library holds more than 100 climate variables to apply for analysis that can be combined with other data models, including finance, supply chain, and service data. Moreover, in 2018, Vestas further expanded its big data analytics capabilities and accelerated its digitalization goals from the acquisition of the company Utopus Insights Inc. The acquisition was considered an important contributor for Vestas to provide its customers with innovative digital services as Utopus had extensive energy analytics experience.

In Vestas, big data analytics's value may come from combining a variety of data in real-time. This includes performance data, meteorological measurements, IT performance logs, turbine data, SCADA, and security data. Bringing these data together in big data analytics projects to develop solutions that support decision-making, is key to gaining a competitive advantage in the wind industry. For example, developing data solutions for service technicians that can carry a digital device, allowing them to make data-driven decisions in the field. Vestas works with descriptive analytics that visualizes the data, predictive analytics to pre-empt and pro-actively handle costly turbine faults before they take place, and prescriptive analytics, which is advanced analytics such as machine learning.

Essentially, big data analytics is evident within Vestas, and the organization has deep knowledge in developing big data analytics technologies. However, Vestas still face major benefits challenges in its big data analytics efforts. The first study of the PhD dissertation outlines this (Jensen et al., 2019), taking the offset from big data analytics projects and what challenges are associated with this in realizing benefits. This PhD has then addressed this concern from different perspectives leading to a holistic understanding of how organizations can address this concern in practical terms.

1.4. RESEARCH QUESTION

In practice, materializing benefits from big data analytics has become a key concern for many organizations embarking on incorporating big data analytics into organizational decision-making. As previously explained, there are many potential benefits that big data analytics may provide, yet organizations struggle with how to move past the technologies. A recent report by Gartner forecasts that through 2020, 80% of big data analytics projects will not deliver any business benefits or make it into production (White, 2019).

Several scholars are beginning to address the necessity for research on big data analytics that is concerned about the context in which big data analytics materialize as a benefit. Numerous approaches and theoretical framings have been presented, yet knowledge about the topic is still scattered.

This dissertation proposes a benefits management and a systems heuristics perspective on the topic to provide an integrative understanding and a basis for dealing with big data analytics benefits. First, benefits management was developed from the IS/IT perspective to solve the challenges for these types of projects in delivering the promised value to the organization (Ward and Daniel, 2012). The benefits management approach focuses on accurately identifying benefits and planning to realize these. The approach is *"the process of organizing and managing so that the potential benefits from IT are actually realized"* (Ward & Daniel, 2012, p. 8). Stemming from IS/IT, the benefits management approach is reasonable in trying to apply to big data analytics and specifically for big data analytics projects despite the differences compared to these types of projects towards IT projects. The key point is that benefits management succeeds in incorporating the benefits focus into the approach starting from the project level and that benefits do not materialize from the technology implementation solely. Big data analytics research has focused on the technologies and how to make these work for the organization investing in them. Yet, as has been reported, a significant amount of organizations' big data analytics projects fail (Marshall *et al.,* 2015). Therefore, this dissertation proposes a new perspective to big data analytics projects incorporating parts of the benefits management approach.

Second, Mark *et al.*, (2014) present how IS are social systems that are technically implemented. A socio-technical evaluation is needed for IS, as purely assessing the technical aspect will lead to a meaningless inference. This is because only focusing on the technology will hinder insights into the social activity embedded in the organization. For big data analytics, several scholars address the need to assess big data analytics benefits as the combination of people, process, and technology (Mikalef *et al.,* 2017; Verma and Bhattacharyya, 2017; Mikalef *et al.,* 2019). This understanding enables using a systems thinking perspective, which is useful for studying a complex system with its different parts and interactions (Waldman, 2007). Systems thinking conceptualizes a phenomenon in its entirety before its parts (Churchman, 1968). For a big data analytics project, or any other project, the ultimate success lies in realizing the proposed benefits. The big data analytics project may deliver a technology or big data analytics output for use in the organization, for example, applying analytics in decision-making processes. The systems thinking perspective becomes relevant for big data analytics, as going from the big data analytics output to a benefit is a transformational dilemma involving both people, process, and technology. This dissertation proposes to regard this transformation as a systemic problem that may contain systems of conflicts in defining what the benefit essentially is and how to make it evident.

With the benefits management and systems thinking perspective as theoretical foundations, this dissertation seeks to answer the research question:

How can we engineer a method for creating benefits with big data analytics projects?

My proposed solution consists of a method and lessons, i.e., a way in which a company can repeatedly solve the complex problem of materializing big data analytics benefits to gain a competitive advantage. It stems from a clear problem to be solved in Vestas as well as a research challenge.

The research is reported in 5 full papers that altogether cover the main research question:

[P1] **Maria Hoffmann Jensen,** Peter Axel Nielsen and John Stouby Persson. Managing big data analytics projects: The challenges of realizing value. *27th European Conference on Information Systems, ECIS 2019,* 2019, p. 1-15

[P2] **Maria Hoffmann Jensen**, John Stouby Persson and Peter Axel Nielsen. From Big Data Technologies to Big Data Benefits (Submitted 2nd review to IEEE Computer. Minor revision)

[P3] **Maria Hoffmann Jensen**, Peter Axel Nielsen and John Stouby Persson. Improving the impact of big data analytics projects with benefits dependency networks (Submitted as a fast track paper to the Scandinavian Journal of Information Systems. Best paper award from Scandinavian Conference on Information Systems)

[P4] **Maria Hoffmann Jensen**, Peter Axel Nielsen and John Stouby Persson. Evident benefits from big data analytics projects: A critical system heuristics approach to boundary judgements. (Submitted to the Journal of Information Technology Case and Application Research)

[P5] **Maria Hoffmann Jensen**, John Stouby Persson, Peter Axel Nielsen. Measuring of benefits from big data analytics projects: An action research study. (Submitted to Information Systems and e-business Management)

In the following chapters, I will outline the research in terms of related research, methods used in assessing the research question, and the contributions of each of the papers. Finally, I discuss how the contributions extend current research on big data analytics benefits and offer novel knowledge on the topic.

2. LITERATURE BACKGROUND

Based on the research question and the challenges outlined in the previous section, the literature background will elaborate on different perspectives on value creation from big data analytics, benefits management, and finally, systems thinking. The research streams have jointly provided the directions for this dissertation.

2.1. PERSPECTIVES ON VALUE CREATION FROM BIG DATA ANALYTICS IN THE LITERATURE

In the 1990s, several studies within IS began to focus on what we know as the information (IT) productivity paradox. The paradox refers to the failure to establish a positive relationship between IT investments and organizational productivity. In time, the paradox was resolved as a consequence of two decades of research suggesting several additional resources such as managerial, intellectual capital, IT infrastructure etc., as required to realize the true value of IT investments (Gupta and George, 2016),

The same paradox could be evident for big data analytics as a "big data productivity paradox." Even though this is not yet coined in such terms within big data analytics value research, the IS research community is likely waiting for it to happen. Given the speed at which organizations across different industries and of all sizes are investing in big data analytics, these organizations would want their big data analytics investments to provide them with a competitive advantage. However, several studies present the challenges and low success rates for big data analytics projects for organizations investing in these (Mithas *et al.,* 2013; Tardio *et al.,* 2015; Jensen *et al.,* 2019; White, 2019).

Barriers to value creation from big data analytics is often attributed to a lack of 1) integration into the decision culture (Foster *et al.,* 2015), 2) data science knowledge and skills (Davenport and Harris, 2017; Saltz and Grady, 2017) or 3) cultivating data-driven leaders and attracting data savvy board members (O'Reilly and Paper, 2012; Fitzgerald, 2014; Harris and Mehrotra, 2014). Essentially, this may be summarizing what we know as capabilities – specifically, big data analytics capabilities (Mikalef *et al.,* 2019). Moving past the early papers studying value creation, these acknowledge that value did not solely materialize from the big data analytics technology (Chen *et al.,* 2012; Marchand and Peppard, 2013). Instead, recent research has begun to focus on both the technologies as well as the intangible aspects of big data analytics value creation (Mikalef and Gupta, 2021). Earlier studies building on data as an organizational resource can be found in knowledge management (Galliers and Newell, 2001; Markus, 2001; Newell *et al.,* 2004), business intelligence (Chen *et al.,* 2012; Foster *et al.,* 2015) and decision support systems (Huber, 1981; Silver and Silver, 2018). Yet these studies did not explicitly theorize about the organizational resources, and organizations remain to struggle to create value from their big data analytics. Essentially we know from previous research that organizations can achieve a competitive advantage by developing their capabilities, and recent studies are beginning to confirm the same for big data analytics (Gupta and George, 2016; Mikalef *et al.*, 2017; Wamba *et al.,* 2017; Y. Wang and Hajli, 2017; Mikalef and Gupta, 2021). For big data analytics value creation, an organization must orchestrate and create a capability of its financial, human, physical, and organizational resources that must be reconfigured according to changing market conditions (Teece *et al.,* 1997; Teece, 2014; Gupta and George, 2016). Even though several studies have addressed big data analytics value creation from the capabilities' perspectives, more research is still needed to understand how big data analytics becomes a valuable asset. In this dissertation, I address this at the big data analytics project level.

2.2. BIG DATA ANALYTICS PROJECTS

As described in the introduction section, big data analytics projects can be complex and of high risk for the organization investing in them due to, for example, their intangible nature. Moreover, they typically span departmental boundaries, where no clear governance or ownership is established (Sivarajah *et al.*, 2017; Sheng *et al.*, 2017; Reggio & Astesiano, 2020). Again, research on big data analytics has tended to focus on the technological aspects of it, for example, improving data models, algorithms, data storage etc. (Chen *et al.,* 2012; Saltz, 2015; Baesens *et al.,* 2016; Lau *et al.,* 2016; Günther *et al.,* 2017). Despite the potential value propositions stemming from big data analytics projects, evidence of organizations succeeding with these projects is scarce (Grover *et al.,* 2020). Essentially, the procedure through which big data is transformed into actionable intelligence is difficult (Sivarajah *et al.*, 2017) and is sometimes managed in an ad hoc fashion in teams, using trial and error to identify the right tools, solutions etc. (Bhardwaj *et al.,* 2015). As big data analytics technologies become more adopted in organizations, there will be a growing need to understand ways of optimally mobilizing the relevant resources toward strategic and operational objectives (Viaene and Van Den Bunder, 2011; Mikalef *et al.,* 2020).

Moving past the technological challenge of big data analytics projects, we find the challenge in relation to the semantics of big data analytics (Günther *et al.,* 2017). The semantics challenge is about finding and meaningfully combining the data, turning them into information, and providing decision support (Dutta and Bose, 2015). Yet, the big data analytics project team can potentially struggle to foresee which ex-ante insights that precisely can be generated (Günther *et al*., 2017). This struggle is due to the granularity and variety of data typically included in these projects. Instead, big data analytics projects are often compared to well-defined scientific experiments or clinical trials and have a shorter duration than traditional IT projects (Marchand and Peppard, 2013). Saltz & Shamshurin (2016) describe how big data analytics projects tend to follow other project methodologies than those originally developed for big data analytics projects and that there is a low level of process methodology in the field.

However, doing so causes issues for the big data analytics projects due to its typical explorative nature in which business requirements are not clearly specified and producing results that can be challenging to validate (Saltz, 2015).

Several methodologies that big data analytics can apply exist: 1) business intelligence methodologies, 2) classical data mining methods and 3) agile principles. Those organizations adopting business intelligence methodologies typically try to adapt them to the particularities of big data analytics projects (Romero and Abelló, 2009; Abai *et al.,* 2013). As the classical business development methodologies are developed from the premise of more structured and stable data, the unstructured and highly volatile data sources in big data analytics projects, deems these methodologies to be a less good fit (Provost and Fawcett, 2013). Instead, some Big data analytics projects apply the more *classical data mining methods,* such as CRISP-DM, KDD, Analytics Canvas, and SEMMA (Angée *et al.,* 2018; Kühn *et al.,* 2018). However, these methodologies follow a waterfall model of development that does not support the more exploratory element of big data analytics. Moreover, these methodologies tend to deal very swiftly with both the organizational and benefits-related elements of big data analytics projects (Shearer, 2000). For example, the CRISP-DM guide provides little guidance on measuring benefits and supporting organizational changes for analytics deployment. As a third option, big data analytics projects can follow agile principles (Fernández *et al.,* 2012; Blockow, 2019). Agile methodologies are iterative and incremental and present a good fit with big data analytics projects and the explorative nature these may have (Larson and Chang, 2016). Agile methodologies can more quickly adapt to changes in requirements and user needs. According to Sfaxi & Ben Aissa (2020), big data analytics require a global view of user needs, which is not substantiated in agile principles as these only consider a limited set of users in incremental development. These methodologies have in common that they essentially do not substantiate a benefit focus from the big data analytics project level.

In addressing this concern, this dissertation seeks to advance on how to incorporate a benefits orientation for big data analytics projects in answering the main research question. In doing so, I address the literature on benefits management and systems thinking which the following section will present. In answering the main research question as to how we can engineer a method for big data analytics benefits realization, the method must accommodate the sometimes scattered and improvised big data analytics-related activities in terms of both technology and intangible characters. Meanwhile, it must also be able to deal with the negotiations of competing perceptions of big data analytics benefits as they arise in practice. Against this backdrop, the following chapters explore benefits management and systems thinking.

2.3. BENEFITS MANAGEMENT

In response to the recurring challenges of realizing benefits from IS/IT implementation, a line of benefits realization and benefits management evolved starting in the 1990s (Breese *et al.*, 2015). For example, Ward *et al.,* (1996) developed a process model in terms of a practical guide to support organizational change processes enabled by technology (Ward *et al.,* 1996). Benefits management research related to the model presented by Ward *et al.,* (1996) has been influential among the different approaches presented within benefits management research (Waring *et al.,* 2018). However, benefits realization and benefits management are terms often used interchangeably within IS research (Breese, 2012; *Flak et al.,* 2015). For clarification purposes, it is important to distinguish between the two terms. Very few studies have clearly defined benefits realization (Ashurst *et al.,* 2008; Ashurst, 2012), which may be one of the explanations as to why there is conceptual confusion about the two terms. Instead, some researchers describe benefits realization as a phenomenon without defining it specifically (Ward *et al.,* 1996; Peppard and Ward, 2004; D. Remenyi, Bannister and Money, 2007).

A more detailed description of benefits realization can be found from the inspiration (Peppard and Ward, 2004; Ashurst, 2012; Jenner, 2012) from which it is presented as when organizational value is generated from the use of IS/IT by succeeding with the necessary changes initiated by stakeholders. In this description, the importance of change is central. Benefits realization occurs when the changes initiated by those involved in the IS/IT initiative generate value in the organization. In this connection, benefits management is then the facilitation of the benefits realization, which ensures that benefits are realized. In providing a definition of benefits management, the one presented by Ward and Daniel (2012) is the definition that is most frequently applied (Waring *et al.,* 2018). According to Ward and Daniel (2012), benefits management is defined as "the process of organizing and managing such that the potential benefits arising from the use of IS/IT are actually realized" (Ward & Daniel, 2012, p. 8). Benefits management then acts as the driving mechanism for managing the necessary change activities, including the stakeholders, required to achieve benefits realization (Ward and Daniel, 2012). In this PhD dissertation, the theory of benefits management has been applied due to how it adopts a benefit focus in managing IS/IT investments. The following section will therefore present the theory in detail and how it has been adopted in relation to big data analytics.

2.3.1. BENEFITS MANAGEMENT – THE MODEL

Ever since the beginning of research into benefits management, several practical methods have been developed and presented, which all have the same basic framework in common: identification, planning, implementation, evaluation and review, and future benefits (Aitken *et al.,* 2015). Examples of the approaches developed include the Cranfield Process Model (Ward et al., 1996), the Benefits

Breakdown Hierarchy (Nogeste and Walker, 2005), the Benefits Realization Capability Model (Ashurst *et al.*, 2008), Active benefits Realization (Remenyi and Sherwood-Smith, 1998) and the Great IT Benefits Hunt (Farbey, Targett and Land, 1994). The benefits management literature has been applied to research published in IS journals for several years and in many forms (Ashurst *et al.,* 2008; Kroll and Proeller, 2013; Maritz *et al.,* 2020) that both reflect its relevance (Flak *et al.,* 2015). It has also been utilized for its potential in evaluating IT/IS investments (Hirschheim and Klein, 2012). The following table 1 presents the various benefits management methods from the pioneers within the research field. The table was originally presented by Breese *et al.*, (2015), to which I added the benefits realization capability model by Ashurst *et al.,* (2008).

Research	**Method**	**Definition of benefits management**
Remenyi et al., (1997)	Active benefits realization	"Active benefits realization focuses on achieving the maximum value from information systems investment" (p. 7)
Thorp (1998)	Benefits realization approach	Benefits realization approach is "a business oriented framework, supported by a set of processes, techniques and instruments which enables organizations to select and manage a portfolio of programmes such that benefits are clearly defined, optimized and harvested" (p. 234)
Bradley (2006)	Benefits realization management	Benefits realization management "is the process of organizing and managing, so that potential benefits, arising from investment in change, are actually achieved" (P. 23)
Ward and Daniel (2006)	Benefits management	Benefits management is "the process of organizing and managing such that the potential benefits arising from the use of IT/IS are actually achieved" (P. 36)
Payne (2007)	Benefits management	Benefits management is "a process that defines the potential business benefits and financial impact of a project and ensures that these are achieved in practice" (p. 3)

Ashurst et al., (2008)	Benefits realization capability model	The benefits realization capability model is a "conceptual model of a benefits realization capability, enacted through competences and underpinned by practices that explicitly support the effective management of benefits" (p. 367)
Melton et al., (2008)	Project benefits management	Project benefits management is "a business process which links the reason for doing projects with the business impact from their delivery" (p. 3)

Table 1: Benefits management methods (Adopted from Breese *et al.,* (2015) and modified with the Ashurst et *al.,* (2008) benefits realization capability model)

As previously stated, the benefits management model presented by Ward *et al.,* (1996) has been highly influential among the different approaches presented throughout the years within benefits management research (Ward *et al.,* 1996). This dissertation adopts the model Ward *et al.* (1996) presented due to its widely acknowledged applicability.

In the mid-1990s, the UK Cranfield School of Management Information Systems Research Centre developed a research program to address the limitations of existing IS/IT investment evaluation approaches. That led to a study of over 100 organizations addressing the existing limitations of their evaluation approaches. Results from the study indicated that many organizations were not satisfied with the current methods regarding how these over-relied on financial business cases or simply failed to include more social aspects in IS initiatives. Finally, the study also revealed that very few of these organizations had an effective process for managing IS/IT benefit delivery (Ward *et al.,* 1996; Ward and Daniel, 2012).

That led to the development of a benefits management process model that approaches IS/IT investment from a lifecycle and iterative perspective. As presented by Ward and Daniel (2012), it compromises five different stages (see figure 1) that each holds different tools and techniques (Ward and Daniel, 2012). Benefits management applies to a wide range of initiatives and does not only focus on implementing technology. Instead, benefits management also addresses the organizational processes and changes necessary to achieve the intended benefits from the organization's IS/IT initiatives.

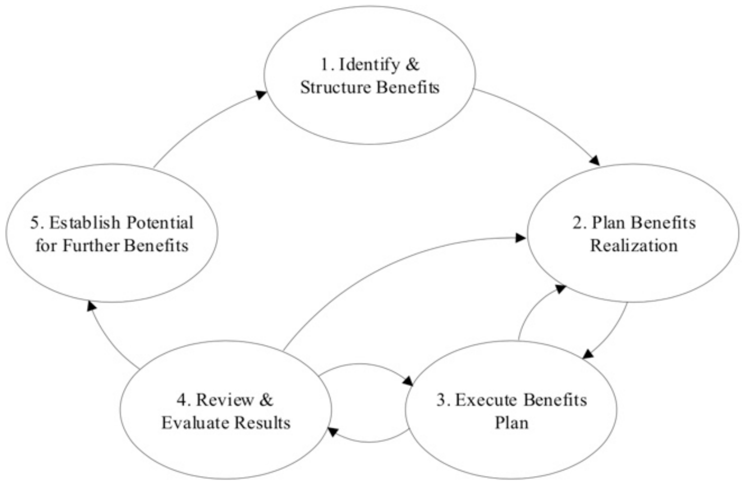

Figure 1: The benefits management process model. Adapted from Ward and Daniel (2012), p. 69

The focus on organizational processes and change is also expressed in the principles that underpin the approach. As presented by Peppard and Daniel (2007), these principles are:

Principle #1: IT has no inherent value. This principle means that simply having a technology will not confer any benefits or create value. IS/IT creates benefits from effective use as the value of it is not in its possession, for example, with real estate.

Principle #2: Benefits arise when IT enables people to do things differently. This principle underlines how IS/IT must support individuals or groups in the organization to perform their roles more efficiently or effectively.

Principle #3: Only business managers and users can release business benefits. As explained by Peppard and Daniel (2007): "Benefits result from changes and innovations in ways of working, so only business managers, users, and possibly customers and suppliers, can make these changes. Therefore, IT and project staff cannot be held accountable for realizing the business benefits of IT investments. Business staff must take on this responsibility" (Daniel *et al.*, 2007, p. 3)

Principle #4: All IT projects have outcomes, but not all outcomes are benefits. This principle conveys the message that many IS/IT projects may produce negative outcomes and that the challenge for managers is to avoid such potential negative outcomes.

Principle #5: Benefits must be actively managed to be obtained: A central and final principle of benefits is that benefits are not outcomes that automatically occur. Moreover, there can be a time gap between the IS/IT investment and implementation until benefits materialize as these require changes in the organization. Thus, managing for benefits does not stop with the technical implementation and instead requires continuous management until the expected benefits have been achieved.

From the principles, it is clear how benefits management stretches into the organizational context, not only focusing on the technical implementation. Ward and Daniel (2012) explain the current situation and the investment objectives the organization has before it begins its' IS/IT investment (Ward and Daniel, 2012). Context is also important when considering the type of benefits themselves. According to Ward and Daniel (2012) "what is considered a benefit will depend on the current performance level of the organization relative to its competitors or business targets" (Ward & Daniel, 2012, p. 235). Essentially the organizational context impacts the type of benefits being identified, which means that it is not possible to develop a set of generic benefits and associated changes for specific types of organizations or similar types of IS/IT investments. Yet, the contextual impact has not gained significant attention in benefits management despite its importance in providing an overall understanding of the scope and expected outcomes before engaging in an IS/IT project applying the principles and model presented in figure 1. In their book, Ward & Peppard (2002) presented an overview of the benefits management context (figure 2):

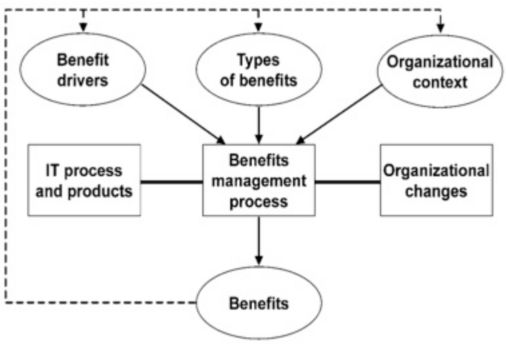

Figure 2: Benefits management context. Adapted from Ward & Peppard, 2002, p. 441

Leaving out the benefits management context may exclude an important pre-understanding of the IS/IT initiative that the organization wishes to invest in. It is unclear why the benefits management context is not an integral part of the pre-stage of the benefits management model and is only available from publications almost 20 years ago.

2.3.2. BENEFITS DEPENDENCY NETWORKS

The benefits dependency network is a central framework in benefits management (Bradley, 2010; Ward and Daniel, 2012). The benefits dependency network is designed to link investment objectives and expected benefits with the needed business changes and IS/IT technology required to realize the benefits eventually. The content in the network is developed from right to left, starting with the investment objectives and then moving through each of the categories in the network to the left. In addition, the network's visual nature reduces ambiguity, confirms clarity of purpose, and aids communication (Aitken *et al.*, 2015).

Figure 3: A benefits dependency network as presented by Ward and Daniel (2012).

Developing the content in the network from right to left drives investments by business demand rather than IT supply. Traditionally, the technologies have driven many projects and approaches. The benefits dependency network explicates how IS/IT investments link to the benefits and that the investment is justified. Thus, the logical dependencies in Figure 3 all point to "Business benefits." Yet innovation-based investments often require evaluating some technologies that initially do not explicitly state their objectives or benefits (Daniel *et al.*, 2007).

We begin with the project's investment objective, which is what supports the vision of the project or initiative. A project may have several objectives that may create several benefits. The investment objectives must be expressed to encourage relevant stakeholders to commit to these. Typically investment objectives are linked to business drivers, which are more long-term and strategic driven as well as related to the external environment of the organization. Each objective ought to link to a business driver. The lack of one will hinder developing a valid business case for the project (Ward and Daniel, 2012). The next category is concerned with the business benefits gained from the IS/IT project. A benefit is defined as "an advantage on behalf of a particular stakeholder or group of stakeholders" (Ward & Daniel, 2012, p. 70). The definition implies that the benefits are owned by either the individuals or groups who want to gain value from the IS/IT investment. A benefits dependency network can hold various types of benefits. These benefits can have different degrees of explicitness, ranging from being observable, measurable, quantifiable, and financial, in which the latter has the highest degree of explicitness. Central in the network are the categories that involve change. First, the category business changes make explicit the new ways of working on a continuous basis to ensure that the desired benefits are realized. These changes are sustained in the organization until the next change initiative occurs. The enabling are changes that are prerequisites for achieving the business changes or "that are essential to bring the system into effective operation within the organization" (Ward & Daniel, 2012, p. 73). The enabling changes are meant to be one-off activities. Finally, the last category in the network relates to the technology to be implemented "IS/IT enablers". Mapping the different content in the benefits dependency network presents the organization investing in the IS/IT project with an enhanced understanding of the dependencies between the organizational context, technology, and benefits and how these are connected.

Since its introduction, the benefits dependency network has been applied to various fields such as software, customer relationship management, and big data analytics (Wilson *et al.*, 2007; Jabbari *et al.,* 2018; Maritz *et al.,* 2020). Typically, the benefits dependency network is applied as a framework for either synthesizing or analyzing some case data. For example, Jabbari *et al.,* (2018) conduct a systematic literature review to characterize DevOps by exploring its central components and synthesizing their findings using the benefits dependency network method (Jabbari *et al.,* 2018). Similarly, Maritz *et al.,* (2020) synthesize big data analytics implementation considerations using the benefits dependency network to structure their findings from a systematic literature review (Maritz *et al.,* 2020). Maritz *et al.,* (2020) describe the benefits dependency network as a tool, which they adopted due to its "powerful visual ability to graphically highlight change requirements, both on a holistic (enterprise) and functional level, that managers can use as a guide to evaluate the extent of changes required prior to embarking on new IT investments, in this instance the adoption of BDA" (Maritz *et al.,* 2020, p. 483). Moreover, they highlight how the benefits dependency network manages to consider the relationship between people, process, and technology to understand how benefits will be delivered by bridging the technology and business. Wilson *et al.,* (2007) conducted a case study about customer relationship management implementation in which they applied the benefits dependency network. Instead of tracking resources over time as a standard way, they mapped a chain of cause and effect from which they established rigor in the thinking associated with implementing and avoiding technology rather than business objectives. Wilson *et al.,* (2007) summarized the usefulness of the benefits dependency network in terms of being economical and political, ensuring identification of necessary changes and enabling better control through appropriate metrics (Wilson *et al.,* 2007). Adding to a more ontological discussion, Pellegrinelli (2011) suggests that benefits dependency networks could be "conceived as instantiations or articulations of shared intent or meaning, subject to interpretation or revision" (Pellegrinelli, 2011, p. 237)

However, despite the benefits dependency network's obvious strengths, it has been criticized for only taking an internal focus on an organization's need to manage its return on an IS/IT investment (Rogers *et al.,* 2008). In their study, Rogers *et al.,* (2008) propose that the benefits dependency network can be extended with an external focus (e.g., a customer focus) by adapting the approach of Shaw's "five perspective methodology" and adding a facilitation framework step to accommodate the need to also focus on employee buy-in. Moreover, as central methods in benefits management, both have been criticized for being mainly anchored within the instrumental approach in which most of the research concerning benefits management belongs. Social and political dimensions are rarely taken into account, nor how benefits management or benefit dependency networks actually work in practice (Aubry *et al.,* 2021)

2.3.3. BENEFITS MANAGEMENT – AS OF TODAY

In their study, Breese *et al.,* (2015) identified four stages in the development of benefits management. In the following, I will describe each of the stages up to where benefits management is today. Understanding the different stages of benefits management and its development is useful in appreciating the nature of benefits management and its applicability.

Stage 1 represents the 1990s, when the early development of benefits management took place. Consultancy firms and business-oriented university departments largely dominated the scene. In this period, the pioneers publishing on benefits management tended to work separately from each other and as consultants advising clients about benefits management, which also meant acting as trainers offering courses on benefits management. Despite them working separately, they developed methods that, in many respects, were quite similar, despite having different names and emphases. Moreover, most of the pioneers were based in the UK except Thorp, (1996), whose clients were largely from Canada, USA and Australia. Different universities were also involved in the early development of benefits management through their inter-linked research and consultancy activities in IT and related fields. Probably the best-known example is the work conducted at Cranfield School of Management (Ward and Daniel, 2012), from which the Cranfield Method was developed and then used by over 100 organizations coming the next ten years both in Europe and in the USA. At this stage, benefits management arose from new types of projects and relatively complex business-related IS/IT investments from which obtaining either no or a marginal benefit was high compared to the engineering and construction fields that previously had the mainstay of project management (Bradley, 2010). As such, several challenges arose concerning benefits management in the first stage. For example, the word "benefit" was not a unique term defined in the benefits management field. It made the term particularly subject to interpretation and malleable when translating it between languages. Moreover, a challenge was evident from the relationship between projects, benefits, and value in which the project had to deliver the needed capabilities that were necessary for benefits realization. However, these capabilities were not sufficient in themselves but had to be combined within a program of projects to maximize value across portfolios of programs.

In stage 2, several scholars and governmental institutions then began to address benefits management in more formal terms by producing policies and procedures. In the early 2000s, government agencies in which benefits management had pioneered began to produce formal guidance that, for example, gave high priority to the value potentially generated by ICT initiatives. Examples of such guidance were the Value Measuring Methodology and the Demand and Value Assessment methodology. Essentially the influence of benefits management began to spread, and it even became mandatory for large parts of the public sector as a key part of the Gateway Review process that was developed in the UK in 2011. Benefits management also began to gain interest from project management professional associations, in which benefits management slowly became incorporated and recommended as a practice in several program and portfolio management processes. Essentially, stage 2, stretching from the late 1990s to mid 2000s, was dominated by how benefits management was consolidated into project management and IS/IT guidance practices. However, several challenges emerged from this consolidation as organizations tried to institutionalize the ideas associated with benefits management. In the mid 2000s, the level of importance given to benefits management by the Project Management Offices was limited which caused the ideas of benefits management not to be acted upon. At this stage, only 28% of Project Management Offices identified benefits management as a part of this function.

Stage 3 stretched from the mid to late 2000s. It was dominated by the examination of the extent to which benefits management had become a project management norm for organizations. In this stage, several new editions of formerly published material concerning benefits management were refined and republished to address some of the challenges. Moreover, within professional bodies, the development of Specific Interest Groups presented the opportunity for consultants, practitioners, and academics to work together in enhancing the benefits management field. Especially the rise of social media, such as LinkedIn, has presented the opportunity for flexible collaboration across a specialist audience of benefits management for beginners within the field. It was also in stage 3 that academic research within benefits management received growing interest. Several studies began to examine the extent to which benefits management was adopted and the effects it had on organizational performance (Lin and Pervan, 2003; Lin, Pervan and McDermid, 2005; Ward, De Hertogh and Viaene, 2007; Ashurst et al., 2008; Haes and Grembergen, 2008; Schwabe and Bänninger, 2008; Naidoo and Palk, 2011). Further, large commercial research organizations such as Gartner published reports on benefits management for ICT investments (Gartner, 2011). Altogether, the general message these different sources tended to convey about benefits management was how it was at a low level of utilization in practice. Moreover, organizations tended not to adopt the full benefits management method but would instead water down the approach (Doherty *et al.,* 2012). From these challenges, research investigating the needed capabilities required for an organization to adopt benefits management fully emerged (Ashurst *et al.,* 2008). Yet, research at stage 3 often found a “knowing-doing” gap (Pfeffer and Sutton, 2000) to exist in which practitioners recognize their inability to emulate good practice (Colin and Hodges, 2010).

Finally, stage 4, starting in the 2010s, was characterized by the development of qualifications specifically for benefits management and its incorporation as a standard requirement in project management education. The qualification development scheme in benefits management represents a further objectification of the management idea by encouraging adherence to a particular set of standards and behaviors needed for passing an exam in benefits management. Breese *et al.,* (2015) conclude their stage and layer model of the development of benefits management with stage 4 and present the stage model as a plausible way of distinguishing qualitative differences in the evolution of benefits management (Breese *et al.,* 2015). The stages above are not to be regarded as a definite categorization of the development of benefits management, and quite some research has been done on benefits management since the study by Breese *et al.,* (2015). However, as noted by Doherty (2014), despite the growing interest in benefits management and its integration into certification practices by various institutions, benefits management is still in its infancy phase (Doherty, 2014).

As of 2015, benefits management has evolved into larger organizational systems (i.e., governance, knowledge) (Aubry *et al.,* 2021). Some recently published research addresses benefits management's relational aspects, such as success factors according to cost, time, and scope (Coombs, 2015; Zwikael and Smyrk, 2019). Others identify challenges and barriers that affect the adoption of benefits management (Semmann and Böhmann, 2015; Terlizzi *et al.,* 2017). Despite normative best practices and various formalized benefits management processes developed from the previous stages, the implementation of benefits management mostly fails to deliver the expected results (Badewi, 2016; Aubry *et al.,* 2021). This has made several studies address the roots of benefits management dedicated to enquiring into its actual practices (Aubry et al., 2021; Fernandes and O'Sullivan, 2021; Holgeid *et al.,* 2021). In referring to actual practice, these studies address the concrete activities that individuals do as they engage in benefits management and the specific challenges, they encounter with this. Thus more recent studies address benefits management with an empirical focus that gives precedence to what is done by practitioners and then building knowledge on the human activities from the situated performance in the local context being addressed. According to Aubry *et al.,* (2021)'s research on benefits management lacks a detailed understanding of the "actual and concrete challenges of doing benefits management" (Aubry *et al.*, 2021, p. 435) and address this in their study by providing an in-depth understanding of the social practices related to benefits management in a project context. The social approach to benefits management is, to a greater extent, concerned with the involvement of various stakeholders required to increase the potential benefits of a project and exploit opportunities it may create. In this approach, benefits are defined as multidimensional multileveled values for different stakeholders with several scholars contributing (Ang and Biesenthal, 2017; Keeys and Huemann, 2017; Eskerod *et al.,* 2018; Liu *et al.* 2019). Essentially the aspect of benefits - multidimensional and multileveled as they are - remains to be studied in greater detail. For future research on benefits management, this means looking into the social, political, symbolic, linguistic as well as emotional elements that may be irremediably bound with the more technical and rational aspects of benefits management (Aubry *et al.,* 2021)

2.4. SYSTEMS THINKING

This section will present systems thinking that has been applied through this PhD study. Systems thinking has been a central instrument in engaging with big data analytics benefits creation from a less instrumental approach described by benefits management. In addition, systems thinking has been particularly useful in thinking about wholes across organizational and departmental boundaries in working with benefits from big data analytics projects.

System thinking revolves around seeing the big picture of the phenomena being studied. It means to view systems from a broad and holistic perspective rather than based on visible interacting variables and specific events. The holistic perspective becomes evident in looking at structures, interactions, behavioral patterns, influences, relationships, cycles, dynamics etc. There exist multiple definitions of systems thinking; however, all have the commonality of including the concept “holistic thinking.” For example, Senge (1990, p. 69) defines systems thinking as “a discipline for seeing the ‘structures’ that underlie complex situations, and for discerning high from low-level change. That is, by seeing wholes, we learn how to foster health. Systems thinking offers a language that begins by restructuring how we think”.

Another definition is offered by Davidz and Nightingale (2008), who state, “Systems thinking is utilizing modal elements to consider the componential, relational, contextual, and dynamic elements of the system of interest” (p. 6). The modal element is the “how” in how the individual performs systems thinking to which various aids can be applied, including tools and methods, different types of thinking, processes, and frameworks (Davidz and Nightingale, 2008). According to Maani & Maharaj (2004), systems thinking is rooted in a cognitive process, and they adopt the notion of systems thinking as a paradigm in their study. The paradigm view refers to systems thinking as a “world view,” seeing things holistically and interconnectedly (Maani and Maharaj, 2004). Finally, Monat & Gannon (2015) identify several notable research works on systems thinking and try to identify and integrate the common themes from the research. They provide a short and coherent definition “Systems thinking is a perspective, a language and a set of tools” (Monat & Gannon, 2015, p. 17) for complex problem solving.

In essence, systems thinking provides great power and value in its ability to solve complex problems that are not solvable by conventional reductionist thinking (Monat and Gannon, 2015). Systems thinking focuses on the relationships among system components and the components themselves. The relationship among the components is often what drives the system’s performance.

Throughout the years, different approaches to systems thinking have been developed. In this dissertation, the soft systems methodology within the interpretivism paradigm and the critical systems heuristics within the critical and emancipation paradigm have been applied. In the following, each of these methods is presented and the reasons as to why these have been applied.

2.4.1. SOFT SYSTEMS METHODOLOGY

Soft systems methodology (SSM) is an approach for appreciating problematic situations and taking action in these as being ill-structured and complex stemming from engagement with real-world problem situations (Checkland, 1989, 1994; Checkland and Scholes, 1990). SSM is regarded as one of the most well-known practical systems methodologies and has been applied in various research types (Van De Water *et al.,* 2007; Mingers and White, 2010).

SSM is based on the idea that organizations can be regarded as systems of purposeful activity that continually bring about change or transformation. Activities are undertaken in the system by actors involved to produce some sort of output, for example, a physical product, service, or information. SSM acknowledges that different stakeholders in a problematic situation may have different perceptions and views (Weltanschauungen) about the nature and purpose of what is being investigated. As such, SSM builds models to reflect the varied viewpoints. The approach is action-oriented and organizes thinking about problematic situations so that action to foster improvement can be taken (Checkland and Scholes, 1990). SSM recognizes that problematic situations arise because different people have different taken-as-given and often unexamined assumptions about the world. These assumptions cause them to regard the world in a particular way. As Checkland (2006) would describe it, *"One person's 'terrorism` is another's 'freedom fighting`; one person sees a prion in terms of punishment, another sees it as seeking rehabilitation"* (Checkland & Poulter, 2006, p. 1). Checkland is referring to how these people have different worldviews and that in dealing with problematic situations, we have to accept this and pitch analysis to a level in which these worldviews can be surfaced and examined. Moreover, SSM acknowledges that people with different worldviews within a given problematic situation, all try to act purposefully. This means that the people will act with intention and not simply by instinct or thrashing about. Simply put, the shape of the SSM approach is as follows;

1. Inquiring into the problematic situation and the characteristics of the intervention in order to improve it. First, characteristics of issues, the prevailing culture, and the disposition of power within the overall situation are assessed. In this initial step, Checkland proposes using Rich Pictures to depict the problematic situation. In making a Rich Picture, "the aim is to capture, informally, the main entities, structures and viewpoints in the situation, the processes going on, the current recognized issues and any

potential ones" (Checkland & Poulter, 2006, p. 25). A rich picture is thus a detailed account of the problematic situation depicted. Moreover, finding out about the problematic situation consists of three further analyses. Analysis one consists of thinking about the intervention itself, asking questions such as "who are in the roles of either client or practitioner?" and "who could usefully be included in the list of issue owners?".

2. Once the problematic situation has been analyzed, the second step in SSM is to design some purposeful activity models that are deemed relevant for addressing the problematic situation. Each of these activity models is based on a particular worldview. Root definitions (RDs) are developed to describe the activity model. To enrich the RDs, Checkland proposes to use the ´PQR formula" in which P is the "what," Q is the "how," and R is the "why": do P, by Q, to achieve R. To enrich the root definitions, SSM presents the acronym CATWOE – Customer, Actors, Transformation, Weltanschauung, Owner, and Environment. Addressing these elements will contribute to defining the RD and a purposeful activity model, a conceptual model of the necessary activities to achieve the desired transformation defined from the RD. The activity model's measures of performance are assessed by three criteria sets – the three E's. These are 1) criteria to tell if the transformation is working, of *efficacy,* 2) criteria to tell if the transformation is being achieved, of *efficiency,* and 3) criteria as to whether the transformation contributes to achieving a higher-level or longer-term aim of *effectiveness.*
3. Once the activity models are developed, these are used to question the real situation of inquiry. It is important to note that these models are not intended to be models of either the organization or the problematic situation how it actually is. Instead, the models depict the activities that would happen if the system transformation and system described in the RD were to be brought into existence. The activity models bring structure to assessing the problematic situation with the aim of finding changes that are both desirable and culturally feasible (Checkland and Scholes, 1990).
4. Finally, the last step in SSM is to define what actions are needed and then take them to improve the situation. However, Checkland notes that this is a continuous learning cycle and that making changes may essentially foster new problematic situations that require intervention.

SSM has been applied in various types of studies. For example, Mingers *et al,*. (2009) apply SSM to structure the inputs and outputs in the hard method approach, Data Envelopment Analysis (DEA). Their study portrays how SSM successfully can be combined with DEA in determining possible performance indicators in evaluating research institutions (Mingers *et al.,* 2009). Rose (2002) applies SSM in an action research study to structure the development of an intranet in a university department. The study presents a systems development concept, the ITI model, that regards systems development as primarily a managerial and social task rather than a technical one (Rose, 2002). Antunes *et al,* (2016) apply SSM within the renewable energy sector in assessing the key drivers of the development of smart grids. They apply SSM to evaluate policies and present a list of fundamental objectives for smart grid investments. In a more recent study, Sharma *et al,.* (2020) applies SSM to address the problematic situation of low “opt-in” rates for Precision Health-Care (PHC) – a promising service on digital health ecosystems or cloud-based solutions. With digital healthcare having entered the stage of big data analytics, large volumes, velocity, variety and veracity of health data is shared among numerous players in an eco-system. However this causes several challenges of cyber-security of sensitive health data as current PHC eco-systems are not capable of justifying when or how the data is used. Based on SSM Sharma *et al.,* (2020) develop as set of design rules for a Blockchain-based PHC (Sharma *et al.,* 2020).

However, despite its wide applicability and adoption, SSM has not been without critique. Several studies address their concerns about SSM and how it needs to evolve to overcome the challenges they identify (Lane and Oliva, 1998; Basden and Wood-Harper, 2006; Mirijamdotter and Bergvall-Kåreborn, 2006). For studies applying SSM, it is the possibility of change in practice, the focus on different stakeholders and their views, and the learning process, which is important for choosing SSM (Mingers and White, 2010). Yet, these determinants for choosing SSM also present several areas of difficulty for the use of it in practice (Jackson, 2001; Pala *et al.,* 2003). For example, SSM is criticized in how it deals with relative views and addresses validity in how it, as a methodology, can be regarded as a learning system (Pala *et al.*, 2003). This is due to that SSM gives little attention to biases in the judgments by those involved and the learning barriers these biases produce. Moreover, SSM does not present any guidelines as to how to identify potentially successful actions to improve the problematic situation, or distinguish successful from unsuccessful actions (Pala *et al.,* 2003). Essentially a large part of research on SSM is concerned about SSM itself, instead of the methodology being applied to complex problems and pluralistic contexts (Van De Water *et al.,* 2007). As the most important instrument in SSM, the conceptual models addressing the problematic situation are representations of an ideal reality but mainly at an explanatory level. Yet, this raise concerns as most research limit themselves to the construction of conceptual models. Again SSM is missing guidance on how to intervene in greater details and as to how in precise terms the intervention and restructuring ought to take place (Van De Water *et al.,* 2007). In being criticized for being unable in guiding practitioners to address the problem of coercion and inability to combine multiple method, critical systems thinking started to emerge (Ulrich, 1983; Jackson, 2001).

2.4.2. CRITICAL SYSTEMS HEURISTICS

In critical systems thinking, ´systems` represent conceptual constructs as opposed to real-world entities. These systems constructs and concepts can support researchers and practitioners in describing and understand complex realities, however with the fundamental divide between systems and reality (Reynolds and Holwell, 2010).

Within critical systems thinking, critical systems heuristics represents the first systematic attempt to provide both a practical framework and a philosophical foundation (Reynolds and Holwell, 2020). Originally developed by Werner Ulrich, critical system heuristics is a framework for reflective practice that is based on practical philosophy and systems thinking (Ulrich, 1983). Like soft systems methodology, critical system heuristics understand systems as being conceptual tools that can be used to learn about reality but not as part of reality itself. However, it is also in this distinction that we find the difference between the two approaches. As described by Reynolds and Holwell (2010) "in soft systems thinking, practitioners are supposed to reflect on their systems conceptions, and feasible interventions to be based on them, by 'comparing' them with the real-world situation perceived to be problematic, CSH interrogates the notion of a 'perceived situation' itself" (p. 251). In making problematic, the situation that is perceived to be problematic, critical system heuristics help practitioners to see past their assumptions underpinning the problematic situation.

The fundamental idea of critical system heuristics is to support the notion of boundary critique, which is a systematic effort to deal with boundary judgments critically. Boundary judgments play a crucial role in assessing the meaning and merits of a given claim, as they condition both ´facts` and ´values` (Reynolds and Holwell, 2020). Boundary judgments thereby determine which empirical observations and value considerations are deemed as relevant and which are excluded. Critical system heuristics deal constructively with tensions between potential opposing perspectives – for example, in professional interventions in organizations. Tension can stem from ´situation` versus ´system,` ´is` versus ´ought,` stakeholders ´stakes` versus ´stakeholding issues` (Ulrich and Reynolds, 2020). In order to do so, critical system heuristics uses 12 different questions. These questions help unfold and make explicit the everyday judgments that we, consciously or not, depend upon to understand and design systems for improving the problematic situation we are in. The questions are presented in table 2:

Sources of influence	Boundary judgements informing a system of interest (S)			
	Social roles (Stakeholders)	*Specific concerns (Stakes)*	*Key problems (Stakeholding issues)*	
Sources of motivation	*1. Beneficiary* Who ought to be/is the intended beneficiary of the system (S)?	*2. Purpose* What ought to be/is the purpose of S?	*3. Measure of improvement* What ought to be/is S's measure of success?	
Sources of control	*4. Decision maker* Who ought to be/is in control of the conditions of success of S?	*5. Resources* What conditions of success ought to be/are under the control of S?	*6. Decision environment* What conditions of success ought to be/are outside the control of the decision maker?	**The Involved**
Sources of knowledge	*7. Expert* Who ought to be/is providing relevant knowledge and skills for S?	*8. Expertise* What ought to be/are relevant-knowledge and skills for S?	*9. Guarantor* What ought to be/are regarded as assurances of successful implementation?	
Sources of legitimacy	*10. Witness* Who ought to be/is representing the interests of those negatively affected by but not involved with S?	*11. Emancipation* What ought to be/are the opportunities for the interests of those negatively affected to have expression and freedom from the worldview of S?	*12. Worldview* What space ought to be/is available for reconciling differing worldviews regarding Samong those involved and affected?	**The affected**

Table 2: The boundary categories and questions of CSH. Adapted from (Ulrich, 1996, p. 44)

The 12 boundary questions, presented in table 2, are asked in an “is” and “ought” mode that contribute to analyzing the what, who and how to address the problematic situation. The questions are divided into four categories to describe the normative content of systems as the sources that might influence how a system is perceived. These are 1) sources of motivation, 2) sources of control, 3) sources of knowledge, and 4) sources of legitimacy (Ulrich, 1987). Altogether, the questions make explicit the everyday judgments on which we rely to understand situations to design systems for improving them. As seen in table 2, critical system heuristics systematically distinguishes between “the involved” and the “affected” in the debate about the planning and design of a system. The involved group could, an example, be the professionals or decision makers in a system’s design (e.g., politicians). In contrast, the affected group are those who then receive the system and are affected by it (e.g., the citizens). The latter is not directly involved in the design of the system. In this distinction, critical systems heuristics presents the notion of boundary judgments from the different viewpoints of each of the stakeholders involved in analyzing facts and values when designing a system (Ulrich, 1996)

Critical systems heuristics have been applied to assess social, organizational, and technological systems (Ulrich and Reynolds, 2020). Within information systems research, several studies have utilized its principles of it as well. Critical systems heuristics considers human intervention and broader organizational aspects pertaining to complex social and technological issues, providing a more critical aspect in developing information systems (Córdoba and Midgley, 2008). For example, Jokonya (2016) addresses the complexity of IT adoption in organizations caused by different stakeholder constituencies. The paper contributes to knowledge of the importance of critical systems thinking during IT adoption in organizations as some stakeholders are marginalized during IT adoption (Jokonya, 2016). The paper's results indicate that essential system approaches can potentially improve the adoption success of IS/IT in organizations by assessing both technical and social issues (Jokonya, 2016). Yet, the paper also addresses how the value of critical systems thinking is enhanced through multi-disciplinarity in addressing complex challenges for IT adoption. Specifically, the paper addresses the Total Systems Intervention approach for critical systems thinking. In their study, Venter & Goede (2017) use critical systems heuristics to analyze the inherently conflicting views and visions held by the various stakeholders involved in a new business intelligence system and the system's business process. As the study focuses on the reflection and exploration of innate conflicting vision of the stakeholders involved in the business intelligence system, critical system heuristics was found useful (Venter and Goede, 2017).

Systems thinking with the use of the SSM and critical systems heuristics approaches is relevant for big data analytics due to how systems thinking can deal with complex systems. Several organizations do not to a complete extent understand how big data analytics become a value asset to which structural and systemic management efforts will be necessary (Armenia and Loia, 2022). Indeed, big data analytics can enhance business decisions and foster several benefits from its implementation, yet, to do so, it needs to be appropriately managed and implemented. In organizations, big data analytics is oriented towards collective intelligence processes that are shared and used by various actors and analytical tools. In itself, big data analytics produce an information statement to be consumed in the organizational setting before it materializes as a benefit (Sharma et al., 2014; Abbasi et al., 2016). As complex systems, organizations consist of a plurality of voices and social/organizational dynamics that shape how organizations and individuals act. Thus, generating big data analytics benefits involves a multifaceted relationship between data, analytical tools, and sensemaking in the organizational setting. To this, systems thinking can provide clarity in enabling thinking in terms of the whole, relationships, dependencies, and patterns that do not isolate the needed actors, big data analytics technology, or organizational setting.

3. RESEARCH APPROACH

Moving on, the coming section describes the research approach and empirical material of this dissertation that seeks to investigate the main research question. The dissertation relies on collaborative practice research, which I will describe in the following section and how I applied either action research or case study designs in the papers.

3.1. COLLABORATIVE PRACTICE RESEARCH

As an industrial PhD, collaborative practice research (CPR) seemed like an obvious choice when deciding what methodology, the PhD should follow due to its focus on leveraging collaboration between practice and research. For the research presented in this dissertation, this focus was crucial as the PhD was rooted in an organization, Vestas. CPR then offered concrete ways and means to leverage the elements between practice and research.

Initially developed by Mathiassen (2002), CPR contains both problem-solving and research cycles that balances both relevance and rigor. The problem-solving cycle aims to increase the practitioners' understanding of the challenge they want to solve and how to do so. In contrast, the research cycle aims to contribute to the body of scientific knowledge for the research in question. Before describing how CPR works in practice, it is important to understand the idea upon which the methodology builds. When conducting research with collaborations in practice, a central challenge is achieving a balance between relevance and rigor (Mathiassen, 2002). Relevance is that the research is useful for practice, whereas rigor concerns whether the research is impeccably sound (Glass, 2001). In his paper, Mathiassen (2002) presents the argument for CPR by critically rethinking key challenges concerning researching practice within information systems research. He does so from a particular research project with the ambition to emphasize relevance, yet without abandoning rigor.

When organizing research projects with practitioners, the challenge is finding ways to combine different qualitative research approaches practically. The different approaches are necessary to support both the drivers and sometimes contradictory goals in such a collaboration (Mathiassen, 2002). Overcoming this challenge is not an easy task. First, practitioners must agree to become objects that are studied and therefore accept that meetings will be tape-recorded, the necessity for them to engage in critical reflections of their practices and be willing to report on failures of these. On the other hand, the researchers must be committed to improving practices and adopt flexible research approaches as the practice they engage in may change and new priorities emerge (Mathiassen, 2002). In CPR, the challenges are overcome by establishing a good research-practice relationship. This is done by basing the research activities on first-hand information and in-depth knowledge about the challenges and opportunities presented in practice. Moreover, CPR structures and manages the research process intending to produce rigorous research results that are publishable. This is done by "collecting data systematically, by applying suitable methods of interpretation, by relating to relevant bodies of knowledge, and by ensuring the ability to reflect critically on the studies situations" (Mathiassen, 2002,. p 329). Yet, the criteria for establishing a good research-practice relationship do not always point to the same direction and instead the researchers need to evaluate on these based on what research approach they choose for the study. In this, we may distinguish between three types of research approaches: 1) Action research, 2) Experiments, and 3) Practice studies (Nunamaker *et al.,* 1991; Wynekoop and Russo, 1995; Mathiassen, 1998). Figure 4 depicts all of the approaches.

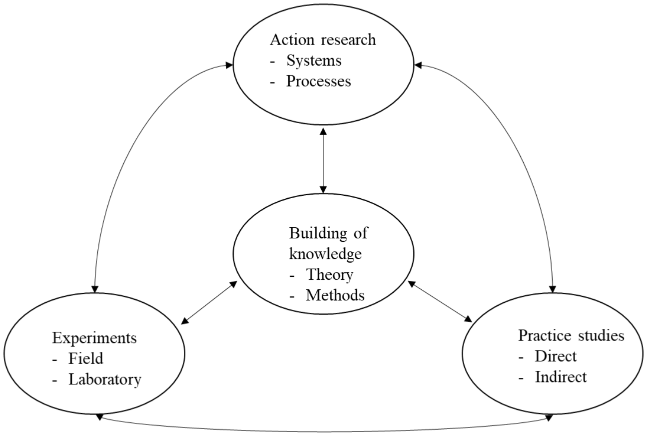

Figure 4: Approaches for studying systems development practice. Adapted from (Nunameker *et al.,* 1991).

In this PhD study, I have applied two of the approaches, action research and practice studies, in the form of a case study, which conforms well to the third lesson presented by Mathiassen, (2002) "Combine action research, experiments, and practice studies" (p. 338). This combination of different approaches is also supported by Mingers (2001), who presents two main arguments as to why we should combine different research approaches. First, as the world we are trying to study consists of a plurality of voices and hence, is ontologically differentiated, pluralistic approaches are needed to deal with the richness of the world. Second, activities associated with research are rarely discrete events but evolve through several phases that each pose different challenges and tasks. Different methods suit each of these stages in different ways depending on the challenges faced by the researchers (Mingers, 2001).

In action research, the aim is to improve practice by intervening with it, whereas in case studies, the aim is to understand practice. For the latter, practice can be studied directly or indirectly. I have been applying a case study approach that studied practice directly. In the following, I will present the action research and case study approach.

3.1.1. CASE STUDY

A case study is an in-depth exploration drawing from different perspectives of a bounded social phenomenon (Stake, 1995; Yin, 2009). Case studies can be applied to programs, organizations, institutions, events, or community and are used across various disciplines. It affords significant interaction with the participants, providing an in-depth understanding and picture of the phenomenon being studied (Yin, 2009). Yin (2018), Merriam (1998) and Stake (1995), three of the major contributors to case study methodology, each offer their definition of what a case study is. First, Yin (2018) presents a twofold definition of a case study as a research method: 1) An empirical method that "investigates a contemporary phenomenon (the "case") in depth and within its real-world context" (Yin, 2018, p. 15), especially when 2) "the boundaries between phenomenon and context may not be clearly evident" (Yin, 2018, p. 15). There exist different types of case studies, as example; exploratory, descriptive, explanatory, and revelatory (Yin, 2018). When to apply the different types depends on the research question, the control the researcher has over the actual behavioral events, and the degree of focus on contemporary vs historical events (Yin, 2018). As for the definition of a case study, Stake (1995) agrees with the rendition proposed by Louis Smith (1978) that researchers should view a case as a system that is bounded and inquire into it "as an object rather than a process" (Stake, 1995, p. 2). Stake (1995) defines case studies as either intrinsic or instrumental and continues to propose that a primary distinction in designing case studies is between multiple or single case study designs. Finally, for Merriam (1998), what defines case study research is the delimitation of the case. She defines a case as a bounded and integrated system in which the case is "a thing, a single entity, a unit around which there are boundaries" (Merriam, 1998, p. 27). Merriam (1998) has a combination of both approaches and distinctions presented by Yin (2018) and Stake (1995). She recommends a flexible design (Merriam, 1998).

What should be evident from this glance at how a case study is defined is that each of the viewpoints presented by Yin (2018), Merriam (1998) and Stake (1995) has made significant contributions to how a case study can be designed. Each of the authors has pros and cons in addressing case studies. In my studies, I have been applying the case study methodology developed by Yin (2018). Based on the research question in [P1] and [P4] I apply an exploratory design in the first paper and a revelatory design in [P4].

Being inspired by scientific methodologies, Yin's (2018) approach to the case study is developed from a desire to maintain validity and rigor in the data (Brown, 2008). In addressing the concerns for balancing relevance and rigor as a PhD study rooted in practice, the attention to documentation of both the research protocol and process presented by Yin (2018) has strengthened the credibility and trustworthiness of the presented studies in this PhD dissertation.

According to Yin (2018) a case study strategy is made up of five components: 1) the question in the study, 2) the propositions that reflect on a theoretical issue, 3) its unit(s) of analysis, 4) the logic that links the data to the propositions and 5) the criteria for interpreting the findings. Conducting a case study then includes preparing for data collection, collecting evidence, analyzing the evidence obtained, and compiling a case study report (Yin, 2018). However, earlier developments in case study methodology by Yin were criticized for having drawn from a substantive and methodological tradition, which as a consequence, disassociates the idea of a case study design relating to fieldwork or participant observation (Platt, 1992). According to Platt (1992) the critique of Yin is due to how he "redefine case study method as a logic of design, seeing it as a strategy to be preferred when circumstances and research problems are appropriate, rather than an ideological commitment to be followed whatever the circumstances" (Platt, 1992, p. 46). Later, Yin refuted the critique and acknowledged the value of a more interpretive perspective (Brown, 2008). Altogether, a case study can provide a rich understanding of a particular phenomenon. Even though the scope of a case study is bounded and its findings in rare cases can be generalized, the methodology is adopted across many disciplines. However, in this PhD, I wanted to collaborate with practice to improve the problematic situation of realizing benefits from big data analytics projects. Thus, in moving from a trying to understand perspective applying case study design, I engaged in action research to ensure relevance and improve practice.

3.1.2. ACTION RESEARCH

A definition of action research that is widely cited is the one given by Rapoport (1970), who states that "Action research aims to contribute both to the practical concerns of people in an immediate problematic situation and to the goals of social science by joint collaboration within a mutually acceptable ethical framework" (Rapoport, 1970, p. 499). The definition by Rapoport emphasizes the collaborative aspect of action research. Referring to earlier works, Lewin (1946), who is typically credited for being the primary developer of action research, stated that action research can "transform unrelated individuals and their interests, into cooperative teams, not on the basis of sweetness but on the basis of readiness to face difficulties realistically, to apply honest fact-finding, and to work together to overcome them" (Lewin, 1946, p. 47).

The very essence of action research is, as such, encapsulated within its name. As described by McKay and Marshall (2001): "It represents a juxtaposition of action and research, or in other words, of practice and theory" (Mckay & Marshall, 2001, p. 47). This description points to how action research is committed to making interventions in real-life practical problem situations, producing new knowledge, and solving the challenges faced by practice (Elden and Chisholm, 1993). What distinguishes action research from other methodologies, for example, case study research, is the active and deliberate self-involvement of the researchers. In the context of the investigation, the action researcher is regarded as a key participant in the research process. Thus, the action researcher works collaboratively with other affected actors, typically the practitioners, to bring about change in the problematic situation that is addressed (Hult and Lennung, 1980). This creates a mutual dependence between the researcher and the practitioner, as these become reliant on each other's skills, experiences and competences, so that the action research can achieve its dual aim of contributing to new knowledge and practical problem solving (Hult and Lennung, 1980). Practically this means that the researcher brings an intellectual framework and knowledge about the research process, whereas the practitioner brings knowledge about the context in which the intervention is taking place (Burns, 1994).

Within IS, action research has many positive features to offer in enquiring into the interplay between technology, humans, information, and socio-cultural contexts. Yet, despite this, action research was largely ignored within IS for a long time, with only a few exceptions. The challenge with action research is that there is a thin line between the researcher doing research or acting as a consultant (Avison *et al.,* 1999). Baskerville (1996) points out that when interventions are successful, it could be argued that causal connections and explanations cannot be made in a safe manner. Moreover, as discussed by Avison & Wood-Harper (1991), researchers doing action research are questioned over a perceived lack of impartiality and bias from the intervention. The critique of action research has put the methodology in disfavor in academic circles that evaluate research according to scientific criteria (Mckay and Marshall, 2001). However, Mckay & Marshall (2001) address the aforementioned concerns in their paper. In considering action research as being composed of the dual imperative of both problem solving and research, they present a new model of action research (Figure 5)

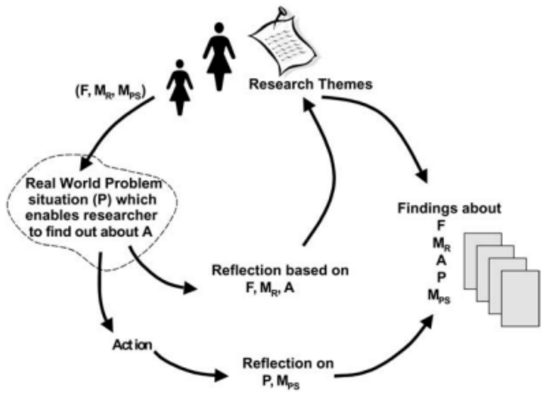

Figure 5: Outcomes of dual cycle action research. Adapted from (Mckay & Marshall 2001, p. 57).

(F: Theoretical framework, M_R: research methods, M_{PS}: Method problem solving, P: Problem situation, A: Issues and challenges in the problematic situation (Area of concern).

This model presents action research as two interconnected and interacting cycles (Mckay and Marshall, 2001). One of the cycles represents and focuses on the research interest in action research (M_R), whereas the other research cycle focuses on the problem-solving interest (M_{PS}). Further, they argue that this distinction between the two cycles contributes to moving action research away from being perceived as merely consulting. Moreover, the model facilitates the researchers in being explicit about the reflection and learning process in action research (Mckay and Marshall, 2001). All in all, action research has been instrumental in this PhD dissertation serving as a valuable research methodology in several of the studies.

3.2. COLLECTING, GENERATING AND ANALYZING EMPERICAL MATERIAL

As an industrial PhD, I often found myself in a bit of a mix in either acting as a researchers or practitioner in Vestas. Throughout the years in Vestas, I naturally became part of several projects that both served as objects for my studies, but in which it also was expected that I contributed professionally. Spending time with the different practitioners and the projects they were involved in, was critical for me in building relationships with these. Especially in the action research studies, in which some sort of change was need. In these, the mutual trust and also learning among me and the practitioners was essential in making intervention in the problematic situation. According to Mathiassen (2002), “the main concern in collaborative practice research is to establish well-functioning relations between research and practice” (p. 329). I also encountered this concern and challenge throughout the years of the PhD in establishing a good research-practice relationship in which my own role sometimes could be blurry for the practitioners. However, being so immersed in the organization setting also had some consequences that sometimes tended to derail the path that I had set for the PhD. Especially when it came to data collection. The following bullet points provides an overview of the data collection period for each of the papers.

- Paper 1. Data collection from March 18 – June 18: Participant observation: 66 meetings, 88 hours total. Documentation: SSM rich pictures, meeting notes, internal documentation of cooperation descriptions btw. Vestas departments, process descriptions of analytics and own observation notes. September 18: Present activity model for analysis. Validated in semi structured interviews guided by the content in the activity model. Recorded and transcribed. Quotes presented in analysis in [P1]
- Paper 2 and 3. Data collection from March 18 – June 18: Initiation phase: Participant observation. 34 hours spread across different meetings in Vestas. Interventions in September 18: Four interventions in Vestas with three different big data analytics projects. Total hours of interventions 34. Researcher evaluation 10 hours. Documentation: Field notes from interventions, project documentation, meeting notes, audio recordings from some interventions and transcriptions of these.
- Paper 4. Data collection from November 19 – August 21: Participant observation: 33 meetings, 51 hours in total. Interviews: 8 interviews each between 60-90 minutes. Audio recordings of each interview and 130 pages of transcript. Documentation: Business case justification material, stage gate presentation documentation, project design specifications, cost & hour allocation material, project task distribution material and meeting notes.
- Paper 5: Data collection from November 19 – August 21: Participant observation in different meetings concerning the case project: More than 51 hours. Interviews: 8 interviews in total between 60-90 minutes each. Audio recordings of each and transcripts. Documentation: Project documentation and business case documentation. Notes from research debrief meetings following each of the interventions. March 22: Action cycle interventions. Data collected from researcher notes in each intervention and audio recordings.

In CPR the research activities ought to be established on the basis of both first-hand information and in-depth insights about the phenomena of investigation (Mathiassen, 2002). It is the responsibility of the researcher to structure and manage the research process in ways that produce rigorous and publishable results. Among different ways, this for example means to collect data systematically. During my PhD study I applied various approaches to collect data. As previously described, I had access to an immense amount of information in different forms that served either as primary data for analysis or secondary data for gaining an understanding of the problematic situation. The primary data, in the forms of interviews, was often easier to structure as these were based on an interview guide that could be strict. Moreover, the interviews were always conducted with a particular aim that was part of a study, which eventually should lead to a research paper. However, structuring the information obtained from participant-observation and documents, as these could come from many sources in different settings, was a challenge. As example, information obtained from project meetings, department meetings, informal talks, subject presentations, PowerPoint presentations etc. Moreover, I would often be invited to meetings for the reason that it *potentially* could contain useful information to the studies I was conducting. Thus the amount of information I was presented towards was a lot. During the time in Vestas, I tried to structure this information in different ways. One approach that I kept applying throughout the entire time was hand-written field notes (Mason, 2002; Patton, 2015). As a rule, I would always carry a piece of paper and a pen to be able to write down thoughts, comments, specific project information, concerns etc. In the beginning I tried to keep two separate logbooks, one that would contain specific information for the PhD studies and one that would contain more general information that was not relevant for the PhD studies. Quickly I found out that this did not work as the information often would be intertwined and keeping two separate logbooks meant a lot more work. Throughout the years this amounted to more than 10 logbooks each with 60 – 70 pages. On some occasions, it was, however, not possible to take hand-written notes in which I instead would write down notes digitally. For some of the studies, I would also voice record my observations and thoughts as a form of debrief after an encounter, as example a meeting. I found this method particularly useful during the action research studies, in which I often would combine this method with my handwritten notes. Finally, internal e-mail correspondences between me and the practitioners in Vestas served as data to inform the different studies I was conducting. As example, in [P5] I had more than 100 different e-mail correspondences with the project manager for the project that was used as case. Finally, the analytical approaches applied in the papers presented in this dissertation involves elements from each of the approached as presented by Mason (2002). In each of the papers I apply or build upon concepts or methods from existing theory, which is the foundation in then considering patterns both across the different data sources involved and within parts of these as well. The data in each of the papers are analyzed based on the research questions presented in each of these. In what follows, I will present each of the papers in relation to their designs: case study and action research.

3.2.1. THE CASE STUDY MATERIAL AND CASES

Beginning with case studies, in his book, Yin (2018, p. 113) presents six sources of case study evidence: documentation, archival records, interviews, direct observations, participant-observation, and physical artifacts. In both of my case studies, [P1] and [P4], I obtain evidence from documentation, interviews, and participant-observation. Being closely involved with the everyday work lives of the practitioners, meant that I had access to an immense amount of data in different forms. Thus, I had to make a clear distinction between what data I applied directly to the two different studies, and what data that essentially was useful, but which was not applied directly in the analysis. An example of the latter would be information obtained in the office halls, or by the coffee machine or from documentation evidence, which was useful in gaining an understanding of what was being investigated, but that was not applied directly in the analysis. Instead, the data that was used for direct analysis was obtained from interviews. Especially [P4] was based on a strict interview guide in going through each of the boundary question as presented by Ulrich (1996). The interview guide can be found in appendix A. Ulrich and Reynolds (2020) recommend a specific order in which the questions are asked, which I adopted in the interview guide as well. Moreover, they recommend that the questions are made more specific towards the setting and the audience to which they are asked. Thus, I tailored the wording of the questions to the specific case in Vestas without diluting the original purpose and intend of the question from CSH. [P1] was guided from the principles established in SSM in the stage that SSM calls comparison. In this stage, the ideal expressed in the activity model is compared to the actual problematic situation. The data that I obtained from this comparison came from asking three different questions to each of the presented activities in the activity model: (1) How is the activity currently performed? (2) How well is it performed? (3) How is the performance measured?

Article 1: Case study concerning the challenges of realizing value from big data analytics projects.

The first study sets the scene in identifying various challenges concerning how to realize value from big data analytics projects. I opted for an exploratory case study design based on the type of research question, which included *what,* in the research question. Moreover I had little control over the behavioral events from the practitioners in Vestas. The study was based on the literature on big data analytics projects and benefits management from IS/IT. Benefits management was bridged to big data analytics to realize any value from the latter. Framing the right analysis, information discovery, and then acting upon the findings is crucial in realizing value. Moreover, benefits management explains the necessity in change of practice based on technology and that value will not spring from the technology itself. Yet, as benefits management was relatively new to big data analytics at the time of the study, the first paper aimed to explicate the challenges hereto. For this, a case study approach was chosen as it addresses a contemporary phenomenon, for example, big data analytics projects, in its organizational context (Yin, 2009). Moreover, the case study approach becomes particularly suited when both research and theories are in a formative and early state.

I collected data through qualitative interviews and through participant observation (Patton, 2015) from several meetings in Vestas at the time of the study. From these interactions, the intention was to uncover relevant actors of how the organizational actors involved in the case experienced the problem area of realizing value from the big data analytics projects. Soft Systems Methodology was then applied as a social science method to ensure that the qualitative data obtained has particular relevance for problem-solving. Soft Systems Methodology was then applied to organize the analysis, which eventually ended up with a conceptual model of activities for realizing benefits in big data analytics projects. Several challenges were unfolded substantiated from the qualitative data in each of these activities.

Article 4 – Defining boundaries for big data analytics benefits

Having developed a method from studies 2 and 3 that outlines the dependencies for big data analytics benefits realization across different domains, the fourth study takes a deeper look at how big data analytics benefits can be bounded. In this article, I argue that going from the big data analytics output once the technology has been implemented to a big data analytics benefit is a transformational dilemma. This is because big data analytics is an intangible product producing information statements, which may be interpreted very differently depending on who the receivers are. The varying interpretations can then cause conflicts in what the benefits are and how they can be realized in the organization. Thus, viewing this as a systemic problem containing systems of conflicts, the fourth study reports from a case study in which I propose to attend to the boundary judgments from those involved in the big data analytics project.

The boundaries are assessed by using Critical System Heuristics (Ulrich, 1987; Ulrich and Reynolds, 2020). Critical system heuristics' boundary categories and questions were applied in a big data analytics project in Vestas, Plant design. Here, I opted for am an revelatory case study based on the research question and the contemporary practice-based problem I engaged in (Benbasat *et al.,* 1987). Moreover, the case study was revelatory (Yin, 2009), as the phenomenon of interest in the study previously had been inaccessible to investigations for two reasons. First due to its novelty and second due to limited accessibility to large organizations. Throughout the case period, I practiced participant observation and conducted several interviews based on the boundary questions from Critical System Heuristics. The interviews were transcribed, and I would debrief with the university supervisors weekly for the internal project meetings concerning Plant design in which I participated (Spall, 1998). The case concerned the Plant design project; however, it became even more specific as the unit of analysis was a particular big data analytics benefit: AEP bias and uncertainty. For this, I made a distinction between the two systems. S1 related to the analytical output produced by the AEP bias and uncertainty improved calculation, and S2 was concerned with the AEP bias and uncertainty benefit. The latter system is about transforming the output from S1 to benefit the organization.

3.2.2. THE ACTION RESEARCH MATERIAL

In [P2], [P3] and [P5] I engaged in action research. As noted by Mathiassen (2002) "Action research provides direct access to practice, but it is quite difficult to control the research process" (p. 330). I found this to be true as well. In these studies, I was involved as a researcher in practical problem solving in which the research agenda was highly dependent upon how the practice evolved in each of the iterations. A major weakness of the action research approach concerns the very little support that is provided on systematic data collection (Mathiassen, 2002). Moreover, it is quite difficult to know in advance what type of data to collect due to the emerging nature of the findings. I tried to overcome these challenges in different ways. First, the interventions in Vestas were all based on a solid understanding on the problematic situation that I established in [P1]. This guided the theoretical foundation (eg. benefits management and the deployment of the benefits dependency network) to be used in each of the action research studies. The interventions were in the form of either a workshop or a meeting, which I sometimes was allowed to record and take pictures from. This then provided me with several audio recordings to be transcribed and used for later analysis. However, keeping field notes during the interventions was also crucial as a mean to collect data. As example, if two participating practitioners in an intervention would discuss a topic relevant for the analysis, I would note my thoughts or comments to their discussion in the moment. Finally, I would debrief after each intervention with my PhD supervisors from which I would also record notes. Debriefing was an important way to step out of the organizational setting and elevate the interventions from specific problem solving in Vestas, to more generalizable findings relevant to research.

Article 2 and 3: Action research studies – going from identified challenges to specific improvements

The second and third study was carried out jointly with several practitioners in Vestas as action research studies. The studies contribute specifically to the calls for research on how precisely organizations can obtain benefits from their big data analytics projects. Thus, adopting an action research methodology (Mckay and Marshall, 2001; Mathiassen, 2002) was useful as it affords the investigation of organizational processes with a particular focus on how practitioners should and can take action. These studies, therefore, presented a research question containing "how" with the aim of presenting a specific method developed from iterating with practice. For big data analytics as a research field, progress has been made at the firm-level of analysis with studies applying different theoretical lenses to understand how big data analytics generate value. For example, studies applying dynamic capabilities and the resource-based view have been made (Mikalef *et al.,* 2020; Mikalef, van de Wetering and Krogstie, 2021). Moreover, the research field has been dominated by case studies that tend to focus on the technological aspects of big data analytics. Instead, this dissertation's second and third study moves to the big data analytics project level of analysis to understand how these can generate value. Action research is a popular method for IS research as it links theory and practice in a cyclic process (Davison *et al.,* 2012). The intention of the process is to create a synthesis of specific knowledge that provides the actors the ability to act and general knowledge useful in similar situations (Baskerville and Wood-Harper, 2016).

In studies 2 and 3, the action research design was (Mathiassen, 2002) very iterative involving various cycles of activities that focus on change through interventions in an organizational context. The problem formulation in the studies was collaboratively formulated between the researchers and Vestas (Nielsen and Persson, 2016). The studies adopted theory and concepts about big data analytics value creation and benefits management as an initial research framework. Specifically, the studies adopted the literature on benefits dependency networks as an initial problem-solving framework (Ward and Daniel, 2012).

Article 5 – Moving towards measurement of a big data analytics benefit

The final study was concerned with measuring the benefits of big data analytics after project development. In this study, theory and understanding of measurement were adopted from Churchman (presented in Ferris, 2006), in which measurement essentially is about obtaining an understanding of the observed so that one can attain a measure of control of what is observed to provide a basis for decisions. Churchman contributed to the theory of measurement by pointing out that measurement requires understanding what one is trying to measure and the many intervening variables that impact what is observed and the representation process. In this study, the observed was related to big data analytics benefits that materialize after project development. In big data analytics research, measuring value has predominantly been to either measure the technology or the big data analytics process. However, for a big data analytics benefit to materialize, an organization must do more than only implement the technology. This also relates to what needs to be measured to understand what we want to observe.

In this study, I adopt an action research approach that was structured over two years (Mathiassen, 2002). I had three interventions with a specific big data analytics project, Plant design, to improve their benefits measurement practices. The premise style of the final study was practical and not theoretical, as I wanted to investigate how practitioners involved with big data analytics projects define measures for the benefits they want to achieve. The inference style was therefore inductive, as the arguments I presented were based on data and evidence from the problem-solving activities.

4. PAPERS

The former chapter described the research approach applied in each of the studies, which led to a total of five articles in my PhD. Starting from the research approach, this chapter provides an overview of the contributions made throughout the PhD study from the five articles. Each of the studies reported in the articles aims to unfold how big data analytics can create benefits and how a method for managing this at a project level could be established. [P1] and [P4] are concerned with understanding a phenomenon. Whereas [P2], [P3], and [P5] are concerned with intervention in a particularly problematic situation and improving practice. Each of the papers falls in the category of either addressing boundaries or dependencies in relation to the main research question of the PhD. First, from [P1], several challenges with realizing benefits from big data analytics projects were found based on developing an activity model applying SSM. The challenges associated with each of the activities in the activity model included:

1. Formulate the overall business case and prioritize actions
2. Appreciate the organizational context
3. Explicate the overall benefits
4. Define benefits measures
5. Understand the benefits' relationships across departments
6. Measurement of benefits and usefulness for end users
7. Manage missing benefits
8. Establish end-users

Each of the papers in this PhD addresses the activities and associated challenges described in the activity model from [P1]. Table 3 provides an overview of this.

[P2] and [P3] addressed activities 1, 3, 4, and 5 by developing the benefits dependency network. [P4], concerning boundaries, addresses activity 2 concerning appreciating the organizational context by applying boundary judgments. Moreover, [P4] addresses activity 8, which contains the challenges related to establishing end-users – "unclear responsibility with dynamic use" and "organization-wide diffusion." As part of the action research study – [P2], I incorporated the benefits dependency network into Vestas's daily big data analytics project work. Through this, the product management team and I linked benefits dependency network output to the business case the project team established. In particular, the benefits dependency network and how Vestas recognizes other types of benefits than those that are financially defined has positively impacted how they manage the business case. [P5] then address activities 4, 6, 7, and 8 as well as the associated challenges. [P1] to [P4] focus on either pre- or in-project big data analytics project development. To ensure that the benefits are realized post-project development, [P5] addressed how to measure big data analytics benefits. All in all, the papers jointly contribute to answering the main research question of the PhD dissertation: **How can we engineer a method for creating benefits with big data analytics projects?**

Activity	Article	Content in addressing activity
Formulate overall business case and prioritize (1)	[P2] and [P3]	Development of benefits dependency network for big data analytics projects.
Appreciate organizational context (2)	[P4]	Boundary assessment.
Explicate overall benefits (3)	[P2] and [P3]	Development of benefits dependency network for big data analytics projects.
Define benefits measures (4)	[P2], [P3]and [P5]	Development of benefits dependency network for big data analytics projects. Lessons on benefits measurement.
Understand benefits' relationships across departments (5)	[P2] and [P3]	Development of benefits dependency network for big data analytics projects.
Measurement of benefits and usefulness for end users (6)	[P5]	Lessons on benefits measurement.
Manage missing benefits (7)	[P5]	Lessons on benefits measurement.
Establish end-users (8)	[P4] and [P5]	Boundary assessment and lessons on benefits measurement.

Table 3: Overview of articles addressing activities from [P1]

4.1. ARTICLE 1: ”MANAGING BIG DATA ANALYTICS PROJECTS: THE CHALLENGES OF REALIZING VALUE”

Research question: “What are the challenges of realizing the benefits of BDA development projects?”

Method: In-depth case study, Soft Systems Methodology

Outlet: Proceedings of the 27th European Conference on Information Systems

We answer the research question by incorporating benefits realization into Vestas's big data analytics development projects. Our related research is thus big data analytics development projects and benefits realization management. In analyzing our data, we follow the Soft Systems Methodology and design a human activity system resulting from an open analysis that provides a unique view of the case organization’s problematic situation. We validate the conceptual model with relevant organizational actors to assess its relevance and usefulness for the problem situation. Further, we evaluated it based on its ability to define challenges and spark debate about “what might be changed.” We ended up with a conceptual model consisting of eight activities and logical dependencies between each activity.

The eight activities track benefits from their early identification in the business case to the decision process they should support and the necessary organizational change. We identify 2 – 3 challenges for each activity, 19 in total. We then relate the activities and associated challenges to existing research on benefits realization management and big data analytics. While both big data analytics and benefits realization management receives growing attention from IS researchers, limited research has investigated how the areas intersect at the level of projects. From this paper, we propose the benefits realization management perspective as an important contribution to the call for a broader spectrum of aspects of big data analytics and specifically, the call for research on the management challenges of big data analytics governance to facilitate the value creation process (Kallinikos and Constantiou, 2015; Markus, 2015; Grover *et al.,* 2018).

There is a limited research focus on how big data analytics capture and create value, which is understood as a transformation of insights into decisions (Sharma *et al.,* 2014). We provide a detailed discussion of activity seven from the activity model and specifically discuss the related challenges (Doherty *et al.,* 2012; Ward and Daniel, 2012). In activity seven we see that the challenge of “no project methodology support” is recognized in (Doherty *et al.,* 2012) as they advocate ongoing review of the achieved benefits and after the project development has ended. However, while they advocate for ongoing review, they do not suggest that it should be included in the project methodology. In contrast, the lessons learned from Vestas is that, if not included in the project methodology, it risks being forgotten. A project methodology would then be able to give support with regard to “what” and “how” questions that need to be answered to do it well. Essentially, the challenge continues as most benefits must be realized after the development project has closed. The benefits realization can then be translated into another project, a follow-up project, but it is not necessarily the best organization of benefits realization management activity residing in the business departments and not in the big data analytics department.

Further, activity seven is in accordance with (Labrinidis and Jagadish, 2012) who call for a deployment process of big data analytics. We argue that the deployment should reside outside of the development process and established in the business department where benefits can be realized. We relate this to the findings by (Larson and Chang, 2016) that change management is needed and similarly addressing that there is management activity and concern after the development project has ended. With activity #7 as exemplary we suggest that the challenges are of more general importance and need to be studies in detail in the future.

4.2. ARTICLE 2. “FROM BIG DATA TECHNOLOGIES TO BIG DATA BENEFITS”

Research question: How can a big data analytics project incorporate a benefits orientation in its development practices?

Method: Action research, specifically collaborative practice research

Outlet: Submitted to IEEE Computer

In the second study, we dive into how an organization can reap the expected business benefits by bridging the chasms between business demands and big data technology. We took a central approach from benefits realization management in the IS/IT setting and assessed its usefulness in big data analytics. Essentially this is explicated in two papers. This paper we aimed at IEEE computer, which is a more practice-oriented outlet.

In this article, we engaged in action research with Vestas to better realize the benefits of big data technologies. We report our findings from the investigation by first explaining what a benefits orientation is for big data analytics projects and how it differs from a traditional IT project’s benefits orientation. Next, we present a big data analytics project on Vestas’ business-critical product screening project, where we introduced a benefits orientation. From this, we present recommendations for working with benefits. The research background stems from a benefits orientation for big data analytics projects. Specifically, we focus on a well-established tool from benefits management: the benefits dependency network. Originally developed from an IT/IS focus, we tailor the tool to a big data analytics project setting and its particularities. A big data analytics project's benefits orientation involves eight dependent domains.

We then apply the big data analytics benefits dependency network to a specific case in Vestas – the product screening project. While the big data technologies were initially the main driver for the project, the challenges of realizing the potential benefits through organizational change became an increasing concern. To explain how the team moved its focus from big data technologies to benefits, we first presented an excerpt of the resulting benefits dependency network, followed by how they created it. From this, we provide specific recommendations for achieving a benefits orientation in these types of projects and guiding questions to establish in-depth content for each domain. Moreover, we provide questions for moving between the domains and define dependencies across these. Specifically, our recommendations to achieve a benefits orientation comes in the form of:

- Distinguish the contributions from different domains to big data benefits.
- Define the dependencies across domains for realizing big data benefits.
- Facilitate continuous rework of the benefits dependency network.

4.3. ARTICLE 3. "IMPROVING THE IMPACT OF BIG DATA ANALYTICS PROJECTS WITH BENEFITS DEPENDENCY NETWORKS"

Research question: How can we improve the realization of benefits in big data analytics projects?

Method: Action research, specifically collaborative practice research

Outlet: Submitted to Scandinavian Journal of Information Systems

The third article was motivated by the lack of understanding and how to unpick the link between deploying big data analytics and how an organization obtains a competitive advantage. As a concern raised by several scholars (George *et al.,* 2014; Constantiou and Kallinikos, 2015), the third study engaged in action research to assess the research question of how we can improve the realization of benefits in big data analytics projects. Moreover, the project level of investigation was an important contributor to establishing the necessity and relevance of this study. As a research field, progress has been made at the firm level of analysis with studies applying the theories of dynamic capabilities and the resource-based view in understanding how big data analytics generate value (Mikalef *et al.*, 2020; Mikalef et al., 2021). Yet, there was a limited understanding of how value is generated from the project level of big data analytics and the dynamics in these going beyond technical considerations (Hughes and Ball, 2020). Much research based on case studies tends to focus on big data analytics technologies (Fosso Wamba *et al.*, 2015; Conboy *et al.,* 2020). Instead, the third study contributes to how an organization can overcome the challenges associated with realizing value at the big data analytics project level, which was scarce at the outset of the study (Chiang *et al.,* 2018; Hindle *et al.,* 2020). As described in the method section of this dissertation, the third study adopted an action research methodology. It included several cycles of developing, applying, and evaluating the benefits dependency network adopted from IS/IT in three big data analytics projects in Vestas. From the iterations and closing of the action research study, we present contributions, specifically lessons, on how value can be obtained from big data analytics projects through benefits realization management practices evolved from IS/IT project benefits realization (Ward and Daniel, 2012).

At the beginning of this study, Vestas was unsatisfied with the benefits realization from the big data analytics projects that they embarked on. Essentially, the project methodology they applied for big data analytics projects did not consider benefits realization, particularly in post-project development. Thus alleviating the problematic situation was not simply a question of using existing big data analytics project methodologies. We needed a new perspective on big data analytics projects and explicitly pursued benefits realization management (e.g., Doherty *et al.,* 2012; Ward and Daniel, 2012; Radford *et al.,* 2014).

From the paper, we present three lessons:

- The first lesson makes explicit that the benefits dependency network is useful for connecting the domains supporting benefits realization in big data analytics projects. The lesson is supported by a development in the method in which there is a new distinction between domains in the network (cf. Figure 6 in the paper). Specifically, the distinction between strategy, data analytics, data provider, and outside enablers for big data analytics projects is supported. These domains then augment the other domains as investment objectives, benefits, sustaining changes, and business changes. The lesson makes contribution to research on big data analytics benefits and benefits realization management. First the benefits dependency network responds to challenges of realizing value in big data analytics (Sivarajah et al., 2017). Further, the lesson corroborate that cross-departmental collaboration is necessary for big data analytics benefits realization (Sfaxi and Ben Aissa, 2020; Mikalef and Gupta, 2021).
- The second lesson makes explicit how embedding the benefits dependency network developed in the paper into the big data analytics project practice is useful. The lesson is supported by a method that the benefits dependency network workshops should be held when crossing major milestones in big data analytics projects. Again, the lesson made contributions to both big data analytics benefits research and benefits realization management. First, The benefits dependency network method is easily embedded and independent of existing project methodology, thus adding to the repertoire

of methods (Shearer, 2000; Sfaxi and Ben Aissa, 2020; Kühn *et al.,* 2018). Moreover, Repeated assessment of dependency networks concurs with Viaene and Van Den Bunder (2011) and Davenport and Harris (2017) that continuous reassessment of stakeholder needs is necessary for big data analytics projects. For research on benefits management, the lesson corroborates that successful benefits management for big data analytics projects as for IS projects needs to be aligned with existing organizational management activities (Ward and Daniel, 2012).

- The third and final lesson is concerned with the facilitation of the benefits dependency network. Essentially, the lesson makes explicit that Using the benefits dependency network method to connect the domains supporting benefits realization in big data analytics projects requires strong facilitation. The lesson is supported by the method that a facilitator with knowledge and competence in the benefits dependency method is central to maintaining a benefits focus for big data analytics projects. For research on big data analytics benefits, the lesson on facilitation adds to Tamm *et al.,* (2013) and Gao *et al.,* (2015) on how to emphasize less tangible benefits. Moreover, it was found that a competent facilitator can help create coherence in a benefits dependency network that extends to changing mindsets (Ransbotham *et al.,* 2016). Finally, the lesson extends the importance of the facilitator capability developed by Ward and Daniel (2012) and Radford et al., (2014) to big data analytics projects.

4.4. ARTICLE 4. “EVIDENT BENEFITS FROM BIG DATA ANALYTICS PROJECTS: A CRITICAL SYSTEM HEURISTICS APPROACH TO BOUNDARY JUDGEMENTS”

Research question: How can a big data analytics project make boundary judgements for the benefits they plan to realize?

Method: Case study

Outlet: Submitted to Journal of Information Technology Case and Application Research

The fourth paper was motivated from trying to gain a better understanding of how to create evident benefits from big data analytics. The term evident, refers to a benefit being both materialized and continuous once the big data analytics project development phase is completed. The argument in the paper is based on that going from the big data analytics output once the technology has been implemented, to a big data analytics benefit is a transformational dilemma. As an intangible product, big data analytics produce information statements that may be interpreted very differently depending on who the receivers are. The varying interpretations can then cause conflicts in what the benefits essentially is and how it can be realized in the organization. Thus, viewing this as a systemic problem containing systems of conflicts, the fourth study reports from a case study in which we propose to attend to the boundary judgements from those involved in the big data analytics project.

The paper addresses the challenge that organizations do not to a full extend understand exactly how best to use big data analytics to improve their business performance. The papers address this from a systemic perspective. Research acknowledges that big data analytics provide an information statement to be consumed in a given setting before it can be materialised as a benefit (Sharma *et al.,* 2014; Abbasi *et al.,* 2016). As organizations consists of a plurality of voices and social/organisational dynamics that shapes the way the organisations and the individuals act, defining big data analytics benefits is complex. Moreover the complexity is also evident at the project level as these consists of semi-autonomous organisational members that interact at many levels of action and cognition furthermore guided by generic constructs and driving mechanisms of the organisation's "this is how we do things" practices (Svejvig and Andersen, 2015). Due to these complexities, defining benefits from big data analytics projects is a complex task that may be inhibited by what we know about organizational boundaries (Eisenhardt, 2005), cognitive limitations (Simon, 1955), and cultural differences (Wenger, 1988). Consequently, a big data analytics benefit is highly dependent upon the organisational setting that process a big data analytics output into meaningful comprehensions (Gandomi and Haider, 2015). Essentially, generating benefits from big data analytics involves a multifaceted relationship between data, analytical tools and sensemaking in the organisational setting. Thereby, big data analytics benefits can be seen as a complex systems involving multiple actors (Armenia and Loia, 2022).

The paper presents an in-depth understanding of big data analytics benefits from a systemic perspective, thus thinking in terms of wholes, relationships, dependencies, and patterns. By attending to the boundary judgments made by the actors involved in the big data analytics benefits realization. The paper presents contributions as to how to make evident big data analytics benefits by attending to:

- *Social roles.* Making big data analytics benefits evident requires different social roles in the organization that goes beyond the boundaries of the roles in the big data analytics project. This finding corroborates the importance of understanding the human component (Mikalef *et al.,* 2020) in big data analytics benefits realization. Further, we corroborate (Barile *et al.,* 2012) that the concept of a benefit may be co-determined by actor's interactions and how these negotiate the boundaries around it.
- *Specific concerns.* From this finding, we make explicit how a benefit from big data analytics manifests in an organization in different ways, at different levels and contexts that go beyond merely delivering the technology

necessary for big data analytics. Instead, it demands alignment of resources and expertise for the benefit to become evident. We respond to the call by (Sharma *et al.,* 2014; Gupta and George, 2016; Mikalef et al., 2018) that resource allocation and orchestration processes must be better understood for big data analytics benefits realization.

- *Key problems (stakeholding issues).* Finally, the last finding of the study portrays key problems in relation to measuring improvement, decision environment, guarantor, and worldview for an evident big data analytics benefit, which expands on previous findings concerning big data analytics challenges (Jensen et al., 2019; Berntsson Svensson and Taghavianfar, 2020)

4.5. ARTICLE 5. "MEASURING ON BENEFITS FROM BIG DATA ANALYTICS PROJECTS: AN ACTION RESEARCH STUDY"

Research question: How can we measure benefits of big data analytics?

Method: Action research

Outlet: Submitted to Information Systems and e-business Management)

The fifth and final study addresses the challenge of measuring benefits from big data analytics projects. The study adopts the view on measurement by Churchman (presented in Ferris, 2006). In his view, measurement is about obtaining an understanding of what is observed so that one can attain a measure of control over it. This is then with the purpose of providing a basis for decisions. In this study, the observed refers to big data analytics benefits that are expected to materialize after project development. Research on measuring benefits from big data analytics is still in its infancy, even though several approaches to measure value are available (e.g. value of IT, value of BI) (Hitt and Brynjolfsson, 1996; Lönnqvist and Puhakka, 2006; Melville *et al.*, 2019). Many studies describe the potential benefits that an organization may achieve from investing in big data analytics. Yet, very few of these present a concrete process, method, or framework that shows how the value is made explicit and achieved (Vries *et al.,* 2016).

From this article, we contribute to the calls for research on measuring big data analytics benefits (Mikalef *et al.,* 2017; Grover *et al.,* 2018). We do so from an action research methodology intending to establish lessons. The theoretical framing of the study was based on big data analytics benefits measurement and benefits management. However, as the literature on how to establish benefits measures for big data analytics projects was scarce, we looked into the literature on performance measures for big data analytics and benefits measurement from IS.

The study was conducted over several iterations with a big data analytics project, Plant design. There was a total of three iterations involving different key participants for the Plant design project but also from departments dependent upon the big data analytics technology and insights the Plant design project would deliver.

The article presents three lessons:

- Benefits require change, and change requires measurement. The first lesson specifics that big data analytics measurement should be established as to where the change in the organization, as a consequence of the big data analytics project, will occur. The first lesson expands on the changing perspective for realizing big data analytics benefits. Typical performance measures for big data analytics either relate to the big data analytics itself or the big data analytics process (Veiga *et al.,* 2016; Veiga *et al.,* 2019; Ali *et al.,* 2019). With this lesson, we support the claim by (Mikalef *et al.,* 2017) that big data analytics benefits measures should be based on context. We then expand on our contextual understanding to include the change of practice that can be brought about due to the big data analytics project.
- The second lesson contributes to establishing big data analytics benefits measurement depending on the types involved in materializing the benefit. With this lesson, we contribute to the call by several studies that big data analytics measurement needs to extend into the business context in assessing performance as well as to understand the users' role in this (Erevelles *et al.,* 2016; Mikalef *et al.*, 2017; Mirarab *et al.,* 2019). Especially for the latter, explicating the users in big data analytics benefits measurement as this lesson presents how defining who can involve different groups of people in the organization and mature over time as the big data analytics project evolves.
- The third and final lesson is about the road to establishing explicit benefit measures. The lesson describes how the level of explicitness, e.g., measures defined in financial terms, cannot stand alone as a financial measurement. Instead, for big data analytics projects, establishing benefits measurement depends on other contextual measures as described in lessons 1 and 2. The third lesson aligns with several studies on how big data analytics benefits manifest by orchestrating technology, people, and organization (Mikalef *et al.,* 2017; Ali *et al.,* 2019). The third lesson adds big data analytics benefits measurement to that orchestration that stretches beyond solely establishing financially attributable measures. Instead, in evaluating big data analytics benefits, we must understand that these investments are complex and difficult to measure with a high degree of explicitness and anticipation. As such, the type of benefits needed for big data analytics benefits goes beyond typical measures for big data analytics as either technology or a process.

5. DISCUSSION

This dissertation aimed to present an investigation into the main research question: "**How can we engineer a method for creating benefits with big data analytics projects?".** The research contributions were each reported in five different papers applying a case study or action research approach. Each of the papers represents either the aim of understanding the phenomenon of interest being big data analytics benefits or making interventions to improve practice and report on the changes. The findings from the papers, lead me to four different propositions with a method to support them, presented in figure 7. I propose that in engineering a method for creating benefits with big data analytics project, we should do so from a systems thinking perspective, attending to dependencies and boundaries for benefits realization. In what follows, I will discuss each of these.

Human systems thinking about

Big data analytics benefits	Dependencies	Boundaries
Understand	Lesson: Benefits realization depends on the domains strategy, investment objectives, data provider, data analytics, org. change and outside enabler. Method: Use benefit dependency network to map dependencies across domains. [P1, P2]	Lesson: Benefits are bounded by social roles, specific concerns and key problems. Method: Use critical system heuristics to uncover boundary judgements. [P4]
Improve	Lesson: Mapping and revisiting benefits dependencies. Method: Facilitate workshops to create benefits dependency networks throughout the project period. [P2, P3]	Lesson: Measuring sets the boundary of benefits. Method: Establish benefits measures as bounded by change, explicitness and actors. [P5]

Figure 7: Human systems thinking about big data analytics benefits

5.1. DEPENDENCIES IN BIG DATA ANALYTICS PROJECT BENEFITS REALIZATION

First, in engineering a method for creating benefits with big data analytics projects, we must attend to the dependencies between different elements that materializes a benefit. Previous research on value creation from big data analytics typically agree that what these describe as value, does not materialize from only implementing the technologies for big data analytics (Chen *et al.*, 2012; Marchand & Peppard, 2013; Ransbotham *et al.*, 2016). In this dissertation, and from the different papers presented I propose that we attend to benefits from big data analytics from the lens of benefits management and with a specific development of the benefits dependency network.

Starting with the name of the benefits dependency network implies that benefits depend on something in a larger network. From Ward and Daniel (2012) we have become familiar with the benefits dependency network developed from IS/IT projects, from the premise that these projects and technologies failed to deliver the promised benefits to the organization investing in them. Both big data analytics and benefits realization management is receiving more attention from IS research. Still, there has been limited research on how these areas intersect at the level of projects, and previous research on benefits management has not considered analytics projects. In the first study, I propose that benefits management can be an important contribution to the broader spectrum of aspects concerning benefits from big data analytics (Constantiou and Kallinikos, 2015; Markus, 2015) and, in particular, how big data analytics create and capture value. For big data analytics development, this value is a transformation of insight to decision (Sharma *et al.,* 2014). In bridging benefits management and big data analytics, I present a benefits dependency network approach tailored to big data analytics projects that now includes additional domains: Outside enablers, Data providers, Data analytics, and Big data analytics strategy. This led me to the first lesson and method supported in this dissertation:

Lesson: Benefits realization depends on the domains: strategy, investment objectives, data providers, data analytics, organizational change, and outside enablers.

Method: Use a benefits dependency network to map dependencies across domains.

Obtaining benefits from big data analytics requires it to be appropriately managed, processed and analyzed to generate knowledge and actionable insights, which is not as straightforward a process as one might expect (Jukić *et al.*, 2015; Sivarajah *et al.*, 2017). Some researchers refer to this as a process challenge entailing a group of challenges that big data analytics projects encounter (Sivarajah *et al.*, 2017). From the tailoring of the benefits dependency network, I propose a solution to address the process challenge that stems from the need to align the right people, technologies, and organizational resources to incorporate a benefits orientation into big data analytics projects. This contribution goes well in hand with the call from Sheng *et al.*, (2017) concerning the need for future research on organizational alignment for big data analytics to create actionable insights. The benefits dependency network developed for big data analytics foster such alignment and supports cross-department collaboration as each domain in the method represents different stakeholders and departments in the organization. The latter supports the proposition by Sfaxi & Ben Aissa (2020) and Mikalef & Gupta (2021) that big data analytics specifically demands cross-department collaboration in creating benefits. Lycett (2013) dives a bit deeper into specific parts of how big data analytics projects create benefits in terms of which approach for information discovery should be applied. Lycett (2013) claim that a big data analytics project needs to combine both an inductive and deductive approach, and if not, then an organization will neglect the needed focus on benefits and value concern for big data analytics projects (Tamm *et al.,* 2013; Gao *et al.,* 2015). Accordingly, the new domains Data provider, Data analytics, and Benefits establish a benefit focus in linking analytics to benefits. The dependencies across the domains represent more than simply the delivery of some results. Instead, these dependencies represent an explicit push or pull from one domain to another in creating benefits. Previous studies applying the benefits dependency network have used it for either synthesizing or analyzing some case data (Jabbari *et al.*, 2018; Maritz *et al.,* 2020). In contrast, I present a development of the method for big data analytics projects that serves as a novel contribution to the academic discussion of how big data analytics projects create value.

Section 2.2 presents several methodologies typically used for big data analytics projects, 1) business intelligence methodologies, 2) classical data mining methods, and 3) agile principles. Each of these methodologies has its pros and cons, yet what they all have in common is the lack of substantiating a benefit focus from the project level. For example, the CRISP-DM guide provides little guidance on measuring benefits and supporting organizational changes for analytics deployment. The CRISP-DM is a process model comprising six phases of a data mining project, their specific tasks, and the relationships between them (Shearer, 2000). It begins with the business understanding, leading to data understanding, then data preparation leading to data modeling, evaluation, and the final deployment. The phases of data understanding, data preparation, modeling, and parts of the evaluation phases are mainly concerned with the project's data technologies and modeling aspects. The business understanding and deployment phases focus on the business objectives, data mining goals, plan for deployment, monitoring, and final project review. These phases and contained tasks are thus more focused on the business requirements for the analytics. Moreover, the evaluation phase contains a task of “determine next steps,” which is about listing possible actions and decisions from the analytical output. CRISP-DM is concerned with benefits in the business understanding and deployment phases. In the business understanding phase, a benefits focus is undertaken in assessing the situation. To complete this task, the methodology asks for an assessment of the “cost and benefits” of the project. Specifically, it is about constructing a cost-benefit analysis that compares the cost of the project with the potential benefits to the business if the project is successful. In the deployment phase, the methodology is concerned with a benefit focus in deciding how the use of the analytical results will be monitored and how the benefits must be measured – where applicable. Yet, what I present from [P2] and [P3] in this dissertation, is that simply having a benefit focus at the outset of the project and once the project is in final closing is not enough. We learned that the requirements for the project, resources, and objectives might change throughout the project's lifetime. Thus it is necessary to revise the benefits dependency network in different phases of the project to ensure successful benefits realization. Also, when it comes to the development stages of the analytics, the organization may risk ending up with a big data analytics technology or type of analytics that did not meet their need in the end. Essentially, CRISP-DM does not focus on benefits in the stages of development.

This led me to argue that although benefits materialize from the organizational use of the information the analytics provide and not from the technical implementation only, a benefits orientation must start at the project level in "setting the scene" as the technical development should be guided by what benefits the organizations wishes to achieve. Essentially, to realize benefits from big data analytics, there exist dependencies between the big data analytics project and the adopting organization/departments, which must be attended to systematically. I argue that the tailored benefits dependency network provides a valid starting point. Yet simply having the method is not enough in attending to the dependencies. For it to become useful, it needs to be embedded into existing project development practices and revisited more than once in the project lifetime. Hence the second lesson and method proposed from this dissertation:

Lesson: Mapping and revisiting benefits dependencies.

Method: Facilitate workshops to create and rework benefits dependency networks throughout the project period.

Moreover, an organization like Vestas does not solely work with big data analytics projects but also produces wind turbines and develops IS/IT and R&D projects. The organization relies on different project methodologies that fit the specific type of project in question. Yet, despite being different types of projects, these may depend upon each other of the project outcome. Based on the different types of big data analytics projects and their dependencies on other projects in Vestas, I found that the method developed worked as a plug-in to these existing practices. As with several organizations, Vestas has invested in agile principles for big data analytics projects over the last few years. For agile principles, Sfaxi and Ben Aissa (2020) present a concern about how these principles only consider a limited set of users. The concern is addressed by the method presented in studies [P2] and [P3], as it starts from benefits by involving various users of big data analytics technology.

Moreover, in one of the iterations, I found that the benefits dependency network must not become a static tool that only is applied once in the lifetime of the big data analytics projects, as the type of benefits and requirements in the project may change as it matures. The latter finding builds upon the notion by Viaene & Van Den Bunder (2011) that to align with changing requirements, continuous rework is needed to incorporate user feedback. The benefits dependency network for big data analytics projects presents both a structured and continuous way to align on expectations from users or beneficiaries. For organizations adopting stage-gate project development principles, it may be particularly useful to revisit the network whenever a gate is crossed in the project methodology. Moreover a strong facilitator is needed in establishing both coherent dependencies and content in – and between each of the domains in the network. The facilitator has a key role in steering the participants through the domains in the network. Previous research on benefits management has not explicitly shown how to facilitate the workshop in which the content in the benefits dependency network is developed (Peppard *et al.,* 2007; Ward and Daniel, 2012). Some research even claims that it has been neglected in big data analytics projects (Tamm *et al.,* 2013; Gao *et al.,* 2015). The facilitation findings contribute to benefits management research (e.g. Peppard *et al.,* 2007; Ward and Daniel, 2012) by presenting the importance of facilitation and how the facilitator must not be a key stakeholder in a specific domain in the networks to avoid bias. Instead, the facilitator role can be found in the project steering committee or among project owners who are not involved in the daily work of the project. In [P2], I present several questions to each of the domains in the benefits dependency network. These questions are intended to support the facilitator in developing useful content in each domain, together with the other participants in the workshop. Peppard *et al.,* (2007) present a series of questions and discuss how the knowledge required to address these questions will be distributed across many people that need to be brought together to provide the answers. For big data analytics projects, I present questions similar to Peppard *et al.,* (2007) but present questions specific to the new domains.

5.2. BOUNDARIES IN BIG DATA ANALYTICS BENEFITS REALIZATION

In section 2.3.2, I address the challenges associated with the benefits dependency network. Despite its strengths, the method has been criticized for only taking an internal focus on managing the return on investment from IS/IT (Rogers *et al.*, 2008). To address this, some research proposes to extend the method with an external focus and add a facilitation framework that focuses on employee buy-in. For the latter, I discuss facilitation as a key support method for developing coherent content in each network domain. Furthermore, I have presented questions about both the content in the domains and the dependencies between these. Yet, in moving past the criticism of the benefits dependency network as being rooted in the instrumental approach (Aubry et al., 2021) of benefits management, I propose critical systems thinking as a valid contribution to attend to the social and political dimensions. In the social approach on benefits management, benefits are defined as multidimensional and multileveled values (Ang and Biesenthal, 2017; Keeys and Huemann, 2017; Eskerod *et al.,* 2018; Liu et al., 2019). Soft and critical systems thinking provides clarity regarding relationships, whole, dependencies, and patterns, which does not isolate the actors, technologies, or organizational setting for realizing benefits from big data analytics projects. This essentially led to the first lesson concerning boundaries in this dissertation:

Lesson: Benefits are bounded by social roles, specific concerns, and key problems.

Method: Use critical system heuristics to uncover boundary judgments.

The point of this lesson is that going from the analytical output that big data analytics produces to a potential benefit can be regarded as a systemic problem that contains systems of conflicts due to different stakeholders' benefits judgments. The varying interpretations of the analytical output can essentially cause conflict in what the benefit is, which then will affect what changes need to be planned in the organization and the potential technology to be implemented as well. Systems thinking and the particular application of critical systems heuristics (Ulrich, 1987) contributed to understanding big data analytics benefits by thinking in terms of wholes, relationships, dependencies, and patterns. In referring to a benefit as being evident, it is clearly understood and maybe even obvious to those involved.

However, very few studies provide a detailed account of how big data analytics benefits become evident, even though multiple papers offer valuable insights on what types of benefits big data analytics may provide (Loebbecke and Picot, 2015; Günther *et al.,* 2017; Mikalef *et al.,* 2020). As reported in [P4], results to each of the boundary categories defined from critical system heuristics (section 2.4.2) concerning social roles, stakes, and key problems, elicit different requirements for how a benefit becomes evident. The notion of negotiating boundaries is interesting as several studies in big data analytics research adopt the logic that if some key resources for big data analytics are in place, they are also orchestrated and leveraged efficiently *(Mikalef et al.,* 2020). Yet, I argue how this assumption is essentially very problematic for big data analytics benefit realization, and instead, benefits are bounded by social roles, specific concerns, and key problems to which we must attend.

As discussed in section 2.1, big data analytics needs to be appropriately managed and implemented for it to create any benefits. Generating big data analytics benefits involves a multifaceted relationship between data, analytical tools, and sensemaking in the organizational setting. From a systemic consideration, I propose that managing benefits realization from big data analytics projects means establishing measurement for benefits. Adopting a systemic view on measurement is explained as obtaining an understanding of the observed so one can attain a measure of control over the observed to provide a basis for decisions (by Churchman, presented in Ferris, 2006).

Essentially, very little research has been conducted about big data analytics benefits measurement from a project level. Instead, several studies have been concerned on what is referred to as performance management (Veiga *et al.,* 2016, 2019). In [P5], however, the focus is placed on benefits which are defined as "*an outcome whose nature and value are considered advantageous to an organization*" (Thorp, 1998 cited in Bennington & Baccarini, 2004 p. 21). Emphasis is thus on the term outcome, and I show how measurements for big data analytics benefits must focus on outcomes, which leads me to the final lesson:

Lesson: Measuring sets the boundary of benefits

Method: Establish benefits measures as bounded by change, explicitness, and actors.

Measuring contributes for an organization to gain control over the benefits they wish to realize. Thus, measuring then also bounds the benefit, as what you are trying to control, is what you are measuring, and what you are measuring, is then what you can control (or try to). As benefits from big data analytics does not materialize from the technical implementation alone, you want to exercise control on the other factors that influence benefits realization. To this, I propose that measurement should be established from change, actors and that then will lead to explicitness. Several studies have been concerned with measurement in the form of technology measures, performance measures of the project, process measurement etc., yet very few actually establish measurement for benefits. It is not that these types of measures or ways of measurement are not important, yet they are means to an end, and the end being benefits. Instead the proposed method in establishing benefits measurement extends previous research on this topic that has typically focused on measurement in relation to the technological aspects of big data analytics or the big data analytics process (Larson and Chang, 2016). In contrast, I propose attending to both the user and business context in establishing measurement as several research has proposed (Erevelles *et al.*, 2016; Mikalef *et al.*, 2017; Mirarab *et al.*, 2019).

6. CONCLUSION

In this dissertation, I present lessons supported by methods to manage benefits from big data analytics projects. The lessons and methods are based on a thorough understanding of the challenges associated with realizing benefits from big data analytics projects based on a systemic assessment of the necessary activities involved. I present and discuss the contributions based on five studies addressing the main research question of this dissertation: How can we engineer a method for creating benefits with big data analytics projects? Each of the studies reported in five different articles presents contributions to understanding the phenomenon of interest in big data analytics benefits and then intervention to develop and validate solutions.

First, I present the benefits management perspective as a potential contribution to the call for facilitating the benefits creation process for big data analytics projects. Then, as a systemic consideration, based on SSM, I present an activity model that includes logical dependencies among several activities for realizing benefits from big data analytics projects. Moreover, I present contributions from each of these to benefits realization management research and big data analytics research.

Then, from understanding the challenges to engaging in change, I develop a method for realizing big data analytics benefits and elicit lessons from this based on previous research. My review of the related literature on the approaches to managing big data analytics projects made it clear that very few of these do not explicitly include a benefit focus. Therefore, I apply a new perspective on big data analytics projects based on benefits management. From several iterations with different big data analytics projects in Vestas, I present a tailored version of the benefits dependency network to fit big data analytics projects. From developing the benefits dependency network, several lessons emerged as contributions.

In engineering a method for creating benefits with big data analytics projects, I present contributions on how to create evident benefits. Based on critical system heuristics, I argue that going from the big data analytics output once the technology has been implemented to a big data analytics benefit is a transformational dilemma. Big data analytics produces an intangible product in the form of information statements, which can be interpreted differently depending on who consumes it. I present contributions on how to make evident benefits from big data analytics by attending to social roles, specific concerns, and key problems.

In continuing to assess big data analytics benefits from a systemic consideration, I present lessons on establishing measurement for big data analytics benefits. Very few studies offer a concrete process, framework, or method that portrays how benefits are made explicit and achieved. Measurement is concerned with understanding what is observed to attain a measure of control over it. As benefits from big data analytics manifest in their organizational use, control measures must extend beyond typical control measures at the project level.

6.1. LIMITATIONS

The contributions of this PhD dissertation do not come without limitations. I acknowledge several limitations regarding the types of research approaches applied in the studies. First, the findings are based on collaboration with a single organization. This narrows the generalizability of the findings, even though the scope includes several big data analytics projects.

Concerning the studies applying action research, the method is often criticized for providing “local solutions to local problems” (Hayes, 2011, p. 16), which does not correspond well to establishing scientific rigor to which neutrality and generalizability are needed. To this, I propose extending the findings to other organizations of different sizes or other big data analytics projects. For the studies applying a case study approach, limitations in terms of generalizability are evident. Instead, it would be fruitful to conduct more studies to enrich our understanding of big data analytics benefits, particularly from cases that have a long-term perspective to follow benefits from early development to materialization.

6.2. FUTURE WORK

I see the research presented in this dissertation as part of a roadmap for future research into several themes. First, I suggest that the challenges identified in [P1] must be studied in greater detail. In [P1], I present several empirical research questions that could contribute to maturing the research area of benefits from big data analytics. These research efforts could adopt engaged problem formulation involving multiple organizations instead of just one, as has been the case in this dissertation. This would further enhance the problem dialogue about big data analytics benefits by increasing these challenges' richness and relevance.

For future research, the lessons concerning the benefits dependency network for big data analytics projects could be expanded upon in transferring these into other organizations and big data analytics projects. Extending the lessons to other organizations would improve their generalizability and potentially conceptualize them further. The same would be relevant for the method itself. For this, researchers could adopt different research methodologies compared to the case study and action research approaches in this PhD dissertation. Instead, future research could turn to Design Science Research and Action Design research in expanding and abstracting the method design with underlying design principles.

Finally, future research on benefits from big data analytics projects should continue to assess these applying systems thinking. In [P4], I applied critical systems heuristics to a specific benefit as a case study. I would encourage future research to extend this research into other domains and cases to gain a more generalizable understanding of how big data analytics become evident, or what challenges are associated with each of the lessons presented in [P4] and [P5]. Future research could also extend the type of study reported in [P4] to other kinds of benefits from big data analytics technologies such as Artificial Intelligence. Systemic boundary concerns should also be assessed in the relations between multiple big data analytics benefits in an organization with competing interests. Moreover, future research should assess the benefits of post-project practices and also explore the usefulness of the lessons on measurement.

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APPENDICES

Appendix A. [P4] Interview guide

Appendix B. Included papers

APPENDIX A. [P4] INTERVIEW GUIDE

Question number:	**Question:**
1. (2) Purpose	*- What ought/is to be the purpose of the AEP bias/uncertainty benefit?* *- Whose purpose are we talking about?*
2. (1) Beneficiary	*- Who ought/is to benefit from the AEP bias/uncertainty benefit?* *- Is this also the intended benefiter?*
3. (3) Measure of improvement	*- What ought/is to be the measures of success of the AEP bias/uncertainty benefit?*
4. (5) Resources	*- What ought/is in control for AEP bias/uncertainty benefit realisation and its success? As example resources, technical systems or alike.*
5. (4) Decision maker	*- Who (eg. Function, department) ought/is in control for the conditions ensuring the success of the AEP bias/uncertainty benefit?*
6. (6) Decision environment	*- What relevant factors for AEP benefit realisation should/is be outside the control of the decision makers?* *- In order for AEP benefit to materialize, what factors should be in/out of this process/work/system?* *- Who ought/is involved in this?* *- Who can close the AEP benefit realisation down if it does not provide the intended benefit?*
7. (8) Expertise	*- What ought to be/is the types and levels of competent knowledge and experimental know-how for AEP bias/uncertainty benefit realisation?*

8. (7) Expert	*- Who ought to/is providing relevant knowledge and skills for AEP bias/uncertainty benefit realisation?*
9. (9) Guarantor	*- How might such expert support prove to be an effective guarantor?; a provider of some assurance of success?* *- What ought to be/is the assurances of successful AEP bias/uncertainty value realisation?*
10. (11) Emancipation (to free from constraint)	*- Those potentially negatively affected by the AEP bias/uncertainty benefit, what ought to be/is the opportunities for them to express their concerns and how they see AEP bias/uncertainty benefit realisation?*
11. (10) Witness	*- Do you see that the AEP bias/uncertainty benefit could affect some people or other departments negatively?* *- Who are the victims of the AEP bias/uncertainty benefit? - and the way that it becomes a benefit?* *- Who would take the concerns/non-benefiter from the AEP bias/uncertainty into their responsibility? - why would they regard themselves capable of doing so?*
12. (12) Worldview	*- How should we deal with conflicting opinions of how AEP bias/uncertainty benefit is materialized?* *- What actions ought to happen as a result?*

APPENDIX B. INCLUDED PAPERS

[P1] **Maria Hoffmann Jensen,** Peter Axel Nielsen and John Stouby Persson. Managing big data analytics projects: The challenges of realizing value. *27th European Conference on Information Systems, ECIS 2019,* 2019, p. 1-15

[P2] **Maria Hoffmann Jensen**, John Stouby Persson and Peter Axel Nielsen. From Big Data Technologies to Big Data Benefits (Submitted 2nd review to IEEE Computer. Minor review)

[P3] **Maria Hoffmann Jensen**, Peter Axel Nielsen and John Stouby Persson. Improving the impact of big data analytics projects with benefits dependency networks (Submitted as a fast track paper to the Scandinavian Journal of Information Systems. Best paper award from Scandinavian Conference on Information Systems)

[P4] **Maria Hoffmann Jensen**, Peter Axel Nielsen and John Stouby Persson. Evident benefits from big data analytics projects: A critical system heuristics approach to boundary judgements. (Submitted to the Journal of Information Technology Case and Application Research)

[P5] **Maria Hoffmann Jensen**, John Stouby Persson, Peter Axel Nielsen. Measuring of benefits from big data analytics projects: An action research study. (Submitted to Information Systems and e-business Management)

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