6-17-2021

Improving the Impact of Big Data Analytics Projects with Benefits Dependency Networks

Maria Hoffmann Jensen
Vestas Wind Systems AS, Aalborg University, mahj@cs.aau.dk

Peter Axel Nielsen
Aalborg University

John Stouby Persson
Aalborg university

IMPROVING THE IMPACT OF BIG DATA ANALYTICS PROJECTS WITH BENEFITS DEPENDENCY NETWORKS

Research paper

Jensen, Maria Hoffmann, Vestas Wind Systems A/S, Aarhus, Denmark, mahjn@vestas.com

Nielsen, Peter Axel, Aalborg University, Aalborg, Denmark, pan@cs.aau.dk

Persson, John Stouby, Aalborg University, Aalborg Denmark, john@cs.aau.dk

Abstract

Big data analytics is regarded as the next frontier in creating digital opportunities for businesses. Analytics projects rarely deliver the intended benefits for the organisation that invest in these data analytics, and currently, no widely accepted design method for analytics projects exists. To address this, we report from an action research project in an organisation highly involved with big data analytics and how benefits materialize from these projects through the practices of tailored and focused benefits management. We argue for using the benefits dependency network for orchestrating commitment to benefits. Benefits dependency networks create linkages between analytics technology, organisational change activities, stakeholders' interests and to-be benefits of a project. With this study, we contribute with: (1) a tailored technique for benefits dependency networks, (2) focus on benefits into established project development practices for big data analytics (3) facilitation as a key capability in developing a benefits dependency network.

Keywords: Big data analytics, Benefits management, Benefits dependency network, Action research

1 Introduction

Big data analytics draws attention from academic and practitioner communities describing it as the next frontier for innovation (Gandomi and Haider, 2015; Marshall, Mueck and Shockley, 2015; Günther, Rezazade Mehrizi, Huysman and Feldberg, 2017). Yet, the value that it potentially can generate has for many organizations been difficult to achieve (Svejvig and Schlichter, 2020). The challenge to extract value from massive volumes of data has been considered paramount to understand the dynamics and social environments of an organisation (Loebbecke and Picot, 2015). Many large organisations have already adopted big data analytics or begun to do so, but even though it can prove as a valuable intangible asset, its adoption poses serious challenges (Tardio, Mate and Trujillo, 2015). According to a worldwide survey, 43% of organisations obtain little or no benefit from big data analytics (White, 2015), and more than half of all such initiatives are unable to achieve their strategic goals (Mithas et al., 2013). Information technology (IT) value creation has been widely researched, and academics and practitioners are now calling for advances in big data analytics research (Chen, Chiang and Storey, 2012; Gandomi and Haider, 2015). Our understanding of how exactly organisations should obtain value from big data analytics is limited (Loebbecke and Picot, 2015; Côrte-real, Oliveira and Ruivo, 2017; Mikalef, Pappas, Krogstie and Pavlou, 2020). Adding to this, a study from IBM shows that only 29% of companies utilizing their big data analytics efforts were successful in obtaining benefits from their projects (Marshall et al., 2015), which certainly leaves room for improvement.

In this paper, we address the benefits concern in big data analytics from real-life projects in an organisation heavily involved with such practices; Vestas Wind Systems A/S (Vestas). We adopt an action research (AR) methodology (McKay and Marshall, 2001; Mathiassen, 2002) as it affords investigation of organisational processes, such as big data analytics value creation, with a particular focus on how practitioners can and should take action. We report an action research study as collaborative practice research (CPR) on big data analytics projects for Vestas (Mathiassen, 2002). With CPR both the practitioners and research concern for big data analytics value research is addressed in the practitioners' situated use and the research concern for the empirically based synthesis of big data analytics value research and benefits realization management as our theoretical lens. Our contribution is on how value can be obtained from these projects through Benefits Realization Management practices evolved from IS/IT projects benefits realization (Ward and Daniel, 2012). We focus on benefits and not solely on value as we regard the benefits term to both encapsulates soft and hard value parameters from big data analytics beyond the typical financial measures. Examples of soft value parameters include user satisfaction and trust in analytical results, whereas hard value parameters involve decreases in cost measures, return-on-investment, efficiency gains etc. A big data analytics project can involve both soft and hard benefits equally important for the project's success. In this study, we collaborated with a group of practitioners engaged in such projects, which led to a joint knowledge interest in the research question: *How can we improve the realization of benefits in big data analytics projects*?

To answer the research question, we first present the research literature on big data analytics projects and benefits realization management, forming our theoretical framing. We utilize the theoretical framing throughout our AR activities in Vestas to show how a benefits management focus in big data analytics projects helps obtain benefits for the organisation and serves as a means of orchestration between big data technology, organizational change activities and stakeholder interests.

2 Related Research

Big Data Analytics is described as huge volumes of numerous observational data used in a decision-making process (Goes, 2014). Some researchers define big data analytics as the procedure of accumulating, consolidating, scrutinizing and exploiting large sets of data from autonomous and heterogenous resources to improve managerial decision making (Sun, Xu, Ma and Sun, 2015). A key aspect of these definitions is that it, in the end, is about decision making. Whether that being from AI in an automated form or embedded in people's daily work in organisations, big data analytics must produce actionable intelligence to create value (Davenport and Harris, 2017).

2.1 Big Data Analytics Projects

The procedure through which big data is transformed into actionable intelligence is difficult (Sivarajah, Kamal, Irani and Weerakkody, 2017). Big data analytics projects are complex, of high risk and demand cross-departmental collaboration in the organisation, which also involves actors with various skills (Sfaxi and Ben Aissa, 2020; Mikalef and Gupta, 2021). When working with big data analytics, it is no longer siloed within one specific department that collects, analyses, and exposes the data to decision-makers, but instead spread throughout the organisation (Sivarajah et al., 2017). Recent studies in big data analytics acknowledge that an organization must develop a firm-wide capability in leveraging big data analytics to realize value(Mikalef et al., 2020). As big data analytics technologies become more adopted in organizations, there will be a growing need to understand the ways of optimally mobilizing the relevant resources towards strategic and operational objectives (Mikalef et al., 2020).

We generally see two main challenges for big data analytics projects: 1) technology related and 2) big data analytics semantics related (Günther et al., 2017). For the first challenge, we know that these projects use data from various sources. Data such as transactional data from ERP systems to external data that can be user-generated, sensor-data and third-party data, adds to the complexity of creating benefits from big data analytics projects. Thus, these projects have to overcome the technology implications of managing these type of data, their variety and the speed in which they are generated (Günther et al., 2017). For the second challenge, once an organisation has succeeded with its big data analytics technology efforts, it must now look into the semantics of finding and meaningfully combining the data, turning it into information and providing decision support (Dutta and Bose, 2015). In addition, depending on the granularity and variety of the data included, the big data analytics project team may struggle to foresee which exact insights can be generated ex-ante (Günther et al., 2017). Big data projects are often compared to well defined scientific experiments or clinical trials and with a shorter duration compared to traditional IT projects (Marchand and Peppard, 2013).

An organisation can approach a big data analytics project either inductively or deductively (Günther et al., 2017). There is a tendency for organisations to collect data without a pre-defined purpose which assembles an inductive approach. This approach begins with the data and then aims at generating an explanation of the investigated phenomena, which allows for discovering previously unknown distinctions or patterns from the data (Shollo and Galliers, 2016). The inductive approach poses a paradox between the time spent to scroll through massive amounts of data without a clear focus, business case or specific identification of benefits arising from the big data analytics project (Tamm, Seddon and Shanks, 2013; Gao, Koronios and Selle, 2015). Here, the deductive approach begins with a general theory and then uses data to test it. A deductive approach may be essential for maximizing the likelihood of benefits realization, but it also comes with the risk of confirmation bias. This occurs when decision makers and analysts specifically look for data to confirm their hypotheses (Bholat, 2015). Instead, the deductive and inductive approach should be regarded in practice, as two ideal approaches to combine in big data analytics projects. The approaches must be balanced and intertwined depending on the influence of pre-existing frames of reference, or mindsets of those who interpret the data (Lycett, 2013). Combining the approaches would resemble an abductive approach in which a big data analytics project would try to gain a better understanding of an observation made through testing and theory application (Paavola, 2004; Locke, Golden-Biddle and Feldman, 2008; Lindberg, 2020).

The inductive, deductive and abductive approach in big data analytics projects are concerned with information discovery from big data (Lycett, 2013; Lindberg, 2020). For a big data analytics project to become successful, we must move away from solely focusing on the data and technology and look into a design method that manages the change in mindset required from the organisation. There is currently no widely accepted design methodology for big data analytics projects, and they thus tend to rely on methods that are tailored to another setting. Big data analytics projects are typically managed with either 1) Agile principles, 2) Business intelligence methods, and 3) Data mining development principles. Each methodology has pros and cons, yet due to the type of data involved, architectural demand and variety of tools in big data analytics, it is difficult to apply them for big data projects, and in the end, the organisation may end up not creating the benefits they were aiming for (Sfaxi and Ben Aissa, 2020).

Many organisations attempt to apply *agile principles* in their big data analytics development (Fernández, Mayol and Pastor, 2012; Blockow, 2019). The agile process is iterative and incremental, which fits well with the environment of big data analytics that contains changing requirements and needs, complex data sources and heterogeneous circumstances (Larson and Chang, 2016). Thus, agile methods tend to be adequate for quickly adapting to source changes and changes in user needs. Agile principles often undertake a more exploratory way of developing big data analytics, which can hinder designing the system when defining conformed dimensions in the big data analytics project. These projects require a global view of user needs, and hence it can be problematic only to consider a limited set of users in the incremental development (Sfaxi and Ben Aissa, 2020).

Others continue with more classical *business intelligence* methodologies and try to adapt these to big data analytics projects (Romero and Abelló, 2009; Abai, Yahaya and Deraman, 2013). Several business intelligence methodologies have been defined in the literature and are categorized as requirement-driven, data-driven, goal-driven and mixed-driven (Abai et al., 2013). These approaches would typically apply to classical business intelligence applications obtaining data from a stable and static source and where the Datawarehouse is centralized and structured with periodic extraxt, transform and load jobs. However, big data analytics projects contain data sources that may be unstructured and generated with high velocity and thus, the classical business intelligence development methodologies provide a poor fit for these type of projects (Provost and Fawcett, 2013).

Instead, big data analytics projects can follow the more *classical data mining methods* such as CRISP-DM, KDD and SEMMA (Angée et al., 2018). Here the main goal is to discover and understand data to deploy adequate data mining models for decision-making. Such methods as CRISP-DM tend to follow a waterfall model of development in which one stage has to be completed before the project can move on to the next. Hence, evaluation of the possible solution will only be achieved at the end of the complete development lifecycle. To this, SAIC has developed a big data analytics process model that extends the CRISP-DM data mining model by incorporating big data analytics technologies into the development stage and applying agile principles (Grady, Payne and Parker, 2017). Yet, these approaches tend to quite swiftly deal with the organisational and benefits aspects of big data analytics projects (Shearer, 2000). For example, the CRISP-DM guide provides little guidance on how to measure benefits and support the change in the organisation for analytics deployment. To this end, a report conducted by PwC states how good practices in creating benefits from data is given by how organisations manage their data governance practices, create robust control and data protection mechanisms, and most importantly, take business needs and goals into consideration that also include the usage of fit-for-purpose data analysis assessment (Sfaxi and Ben Aissa, 2020). The described methodologies do not substantiate a benefit focus in big data analytics projects; however, IS/IT projects' benefits management practice may also support a benefits orientation for big data analytics projects.

2.2 Benefits Realization Management and Benefits Dependency networks

The benefits management approach was developed from trying to solve the issue of IS/IT failing to deliver the promised value to the organisation (Ward and Daniel, 2012; Radford et al., 2014). Traditional project and investment approaches force IT project managers to overstate benefits and not define them accurately to the organisational setting. Instead, the benefits management approach focuses on accurately identifying benefits and planning to realise these. Ward and Daniel (2012) describe the approach as “the process of organising and managing so that the potential benefits from IT are actually realised”. A central tool for benefits management is the *benefits dependency network* supporting the bridging of benefits for users and business managers to technology stakeholders. The *benefits dependency network's* core feature is identifying expected benefits and how these benefits will be realized from an IT project (Peppard, Ward and Daniel, 2007). It entails a detailed plan used to guide actions needed throughout the different stages of the project and review progress and achievements during and after project completion and implementation. As such, the method is not a process model as what we know from CRISP-DM etc. Instead, the benefits dependency network approach links benefits to the technology that needs to be developed with representatives for each of the categories in the network. Thus, it helps to communicate the purpose of the project, link benefits to technology and hence provides a key overview to the team members involved. The method ensures that the business demand for technology development is rooted in the benefits that the business will receive. The first version of the network is typically developed in a workshop with participants for each of the categories in the network.

As the benefits dependency network helps link the overall investment objectives and the requisite benefits with the necessary business changes, it becomes an essential tool in creating a plan for delivering the identified benefits. A benefits dependency network consists of five categories that link IT/IS enablers to the project's overall investment objectives. Typically the network will be constructed over a series of workshops involving stakeholders relevant to each of the categories: 1) IS/IT enablers, 2) Enabling changes, 3) Business changes, 4) Business benefits and 5) Investment objectives (Ward and Daniel, 2012)

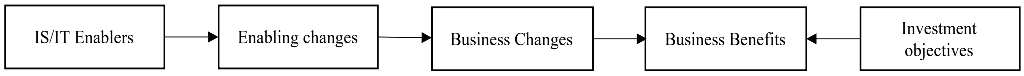

Figure 1 – A benefits dependency network adopted from Ward and Daniel (2012)

The benefits dependency network is built from right to left, starting from the project's investment objectives and not from the technology itself. This way of working drives investments by the business-demand rather than IT-supply, which traditionally has driven many projects and where the approach differentiates from other development methodologies previously described. Furthermore, it explicates how IT investments link to the benefits and that the investment is justified. Thus, the logical dependencies in figure 1 all point to "Business benefits". Yet, for innovation-based investments, it is often required to evaluate some technology that, at first, does not have an explicit objective or benefits stated (Peppard et al., 2007). So, the category "IT/IS enablers" is the technology needed in the project. Central to the benefits dependency network are the two categories that deal with the change aspect: Enabling changes and business changes. The latter refers to permanent changes to the organization such as processes, use of systems/technology, working practices and professional relationships, ensuring that the benefits will be delivered. These business changes depend on the two prior categories of IT enablers and enabling changes, e.g., the new IT system has to be up and running, and the enabling change of training users has to have taken place. Thereby the category "enabling changes" are one-off changes needed to achieve a sustainable permanent change afterwards. These often involve training, agreeing on new roles, redefining work practices, reaching agreements on new responsibilities, identifying redundant systems and establishing new performance management systems. Once the initial benefits dependency network has been constructed, the stakeholders must establish measures and roles responsible for each benefit. Hereafter, changes can be assigned to the right person, and timescales can be established as well. Finally, to ensure the change activities' progress, metrics can be established for each of these and linked to the person accountable for the change (Ward and Daniel, 2012). As such, benefits management may substantiate the value perspective in big data analytics projects.

3 The Action Research Approach

In bridging benefits management to big data analytics projects, we engaged in action research (AR) to address the research question and the need of the client organisation, Vestas. AR is appropriate as our research question addresses how practitioners take action and improve these actions (Baskerville and Wood-Harper, 1998, 2016; McKay and Marshall, 2001; Davison, Martinsons and Kock, 2004). Vestas is a Danish wind turbine manufacturer with more than 25,000 employees worldwide and accounting for more than 20 percent of all wind power capacity globally. Vestas uses big data in various ways to improve the performance of the wind turbines and for decision-making support in the organisation. The organisation is highly experienced in big data and analytics technologies but lacks a benefits focus in its big data projects. As such, this made Vestas an appropriate case for our research.

AR is a popular method in the information systems research community (Davison, Martinsons and Ou, 2012). However, it comes in a dozen forms that all have the shared aim of contributing to scholarly knowledge and improving on organizational problems (Nielsen and Persson, 2016). Our research design was based on the action research approach named collaborative practise research (CPR) (Mathiassen, 2002), which is very similar to Canonical Action Research (CAR) (Davison et al., 2004, 2012). Both approaches are iterative, involving one or more cycles of activities focusing on change through interventions in an organizational context. Thus, the approaches are collaborative with the organizational setting they are in, and work is shared between the researchers and the organizational clients. CPR is, together with CAR, strict in following a cyclical process model as depicted in figure 2.

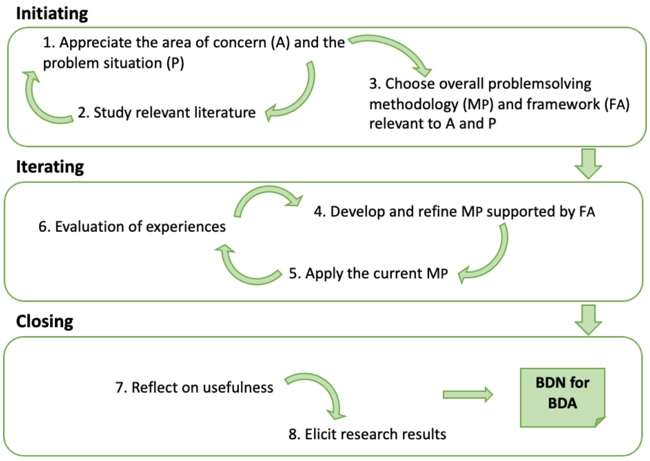

Figure 2: Research Design

However, CPR encompasses a more detailed process model than that of CAR. Thus, CPR offers a research methodology that serves as a general framing of the detailed research design and activities to help us understand current big data analytics and benefits management value practices to improve big data analytics benefits realization in Vestas. Figure 2 is a cyclical process model that operationalizes the dual knowledge interests from the researchers and Vestas. It links the problem-solving methodology (MP) to the framework (FA) that hopefully will be useful in addressing the problematic situation (P) from the area of concern (A) in the client organization. An initial FA was found in the literature on big data analytics value creation and benefits management in big data analytics projects. For MP, an initial problem-solving methodology was found from the benefits realization management literature in benefit dependency networks (Ward and Daniels 2012). The iterative steps in figure 2 (step 4 – 6) are then driven to refine both the benefits dependency network method (Mp) and the understanding of how to manage big data analytics value (FA).

The iterating activities have a joint purpose for the practitioners and researchers to test the benefits dependency network version originally developed by Ward and Daniel (2012) in applying it in various big data analytics projects. Thereby the evaluation was in a real-world setting from which real-world problems concerning big data analytics projects were evident and not something that the researchers could have simulated in a lab experiment or exercise. Thus, our research's premise style is practical through our work with how practitioners create value from big data analytics projects (or not) and how to apply benefits dependency networks in these types of projects.
Our work with big data analytics benefits and benefits dependency networks seeks to contribute with a problem-solving method useful for practitioners in big data analytics benefits creation. Thus, we spend a considerable effort in collecting data and analysing this to develop the problem-solving method. These efforts relate to CPR criterion of documentation from (Iversen, Mathiassen and Nielsen, 2004). Furthermore, the data collection process was supported by the insider-researcher role as the study was conducted as an industrial PhD project. The first author was working in the client organization both before and during her PhD study. Thus, she was already immersed in the organization and obtained a pre-understanding from being an actor in the big data analytics projects and department reported from here. Hereby, we gained access to data at various levels in the organization and the big data analytics projects. We collected data using the following techniques:

- Audio recordings of workshops between the researchers and practitioners
- Researchers individual research diaries
- In-depth qualitative interviews as part of the diagnosis and assessment of usefulness stages.
- Text analysis of BDA project documentation and business cases in the client organization.

- Participant observation from various meetings in the client organization, such as department meetings and strategy workshops.

We integrated the analysis of all the collected data into the AR process. We had continuous feedback in our collaboration with the client organization as results were presented, and as the insider-action researchers implemented the successful changes in the client organization. Table 1 outlines the research activities as described in our research design.

Research activity	Contents	Participants	Hours of collaboration
Initiation	Problem analysis, clarifying challenges, setting the scene, study relevant literature.	Data scientists, project managers, head of department, chief specialist, product managers.	34
I1 - Develop	Application of benefits dependency network method by Ward & Daniel.	Researchers.	
I1 - Apply	Alpha: Apply method in workshop Beta: Apply method in workshop	Data scientists, project managers, product managers, project customers, technical leads and researchers.	4 4
I1 - Evaluate	Elicited from participants' statements		2
I2 - Develop	Method with a new domain "BDA Strategy"	Researchers.	2
I2 - Apply	Alpha: Apply method in workshop Beta: Apply method in workshop	Data scientists, project managers, product managers, project customers, technical leads and researchers.	3 3
I2 - Evaluate	Elicited from participants' statements		2
I3 - Develop	Method with a new domains "Data provider" and "Data Analytics"	Researchers.	2
I3 - Apply	Alpha: Apply method in workshop Gamma: Apply method in workshop	Data scientists, project managers, product managers, project customers, technical leads, head of department and researchers.	3 4
I3 - Evaluate	Elicited from participants' statements		2
I4 - Develop	Method with a new domains "Outside Enablers"	Researchers.	2
I4 - Apply	Alpha: Apply method in workshop Gamma: Apply method in workshop	Data scientists, project managers, product managers, project customers, technical leads, head of department and researchers.	3 2
I4 - Evaluate	Elicited from participants' statements		2
Closing	Incorporation into existing project development practices. Interviews with key managers on effects and usefulness of resulting method.	Senior data scientist, Head of Data & Analytics department, Vice President for Analytics, project customer and researchers	4
Closing	Elicitation of results in academia and practice	Researchers	3

Table 1: Research activities

The research activities followed the steps outlined by the research process model figure 2. The researchers were involved with three different analytics projects in Vestas during the intervention: project *Alpha, Beta* and *Gamma*. The projects involved different stakeholders and departments but were all characterized by having to combine and utilize large amounts of data across various departments in Vestas to extract analytical insights. The *Alpha* project was complex in its setup as it involved multiple sources of data that were rooted both outside and inside of Vestas. The project aimed to combine these multiple data sources to provide analytical insights to senior managers in deciding upon product roadmaps 5 and 10 years into the future. The *Beta* project was rooted in the service department with the objective of enhancing the service applications used by the wind turbine service technicians across the globe. This objective was to be achieved by integrating already established business intelligence applications and combining the analytics results to support the service technicians in their daily work. The final project *Gamma* had the objective of enhancing the value offered from wind turbine power plant concerning the amount of energy the plant produces, the certainty of production predictions and loads estimations of the turbine components. The project combined various wind farm flow, production and load control data to optimize the power plant's lifetime management.

In the study's initiation phase, several challenges were diagnosed in detail using the Soft Systems Methodology (Checkland and Scholes, 1990) to assess the challenges faced by Vestas. The researchers followed several analytics projects to provide a detailed diagnosis of the problem situation. The problems were diagnosed based on participant-observation and qualitative interviews over six months, covering 66 encounters between 1 – 2 hours each (Jensen, Nielsen and Persson, 2019).

4 Research Activities

4.1 Initiating

Based on the detailed diagnosis and a joint discussion of the problem situation, together with relevant stakeholders in Vestas, we identified benefits realization management as a key concern in analytics projects. The two parties jointly initiated improvement activities for benefits management in analytics projects. Together with key stakeholders in Vestas, we considered the issues of 1) making benefits realization management fit for analytics projects, 2) benefits realization in analytics projects accessible for practitioners and 3) the limited empirical knowledge of value realization in big data analytics projects. We adopted the benefits dependency network methodology (Ward and Daniel, 2012; Radford et al., 2014) because of its operational qualities for analytics projects, its easy integration to already established analytics development practices, and its fit with already established development methodologies in Vestas.

4.2 Research Iterations

We had a total of four iterations in Vestas (see table 1). The Alpha project continued throughout all of the four iterations, whereas the Beta project followed the first two iterations and the Gamma project followed iteration 3 and 4.

4.2.1 Iteration 1

In the Alpha and Beta projects' feasibility phase, where they define the scope, costs and value propositions, we applied the benefits dependency network containing the original five categories (see figure 1) in two workshops. We began with the Alpha project workshop in which members representing each of the benefits dependency network categories were present. At the workshop, the researcher presented the benefits methodology and facilitated the team members' work with the categories. As advised from the benefits dependency network literature, we started from the right in the network and then worked our way through each category from right to left. Thus, ending with the IS/IT enablers. The researcher guided the participants in what type of content each of the categories should contain.

Figure 3: Alpha project team workshop

We then continued with the Beta project in a separate workshop session. The Beta project consisted of two separate teams and digital applications that now had been integrated. Through this integration of analytical systems, the users would be better informed in their decision-making processes and only use one application. As with the Alpha project, the researcher facilitated the workshop and guided the participants about each category's content. In contrast to the Alpha project, the Beta project did not share a shared vision for the project at the outset of the workshop session. This lack of a shared vision created conflicting intentions about the Beta project's objectives. We ended each workshop with an evaluation. We found that it already in its initial form had a positive effect in moving the focus from being solely on technology towards benefits and presenting a structured manner in going from benefits to technology. As stated by the senior project manager:

"Building a network has enormous appeal, as it is very structured and help us outline benefits, which historically we have been bad at" (Senior project manager, Alpha project)

On the negative side, it became evident that the project teams needed a category in the benefits dependency network that would elevate the focus from operating solely at the project level to a strategic level for big data analytics:
"We lack the category in setting out the long-term plan for our BDA projects to guide our current project work" (Technical Lead, Alpha project)

The strategic level should guide the project teams in justifying their investment and development actions. At the outset of the Beta project workshop, it became clear that the project team needed to agree on a strategic vision for the two digital applications coming together in order to develop relevant content in the network. The researchers, therefore, included it as a category in the network during the workshop. It had a clear positive impact on aligning Beta's two teams to being one joint team with a shared strategic vision. We thus modified the benefits dependency network from its initial form (see figure 1) to include a new domain *Big data analytics strategy* to the right in the network (see figure 4). We changed the definition in the network from categories to domains to convey that the benefits dependency network operates at different levels in the organisation and across organisational boundaries – as in the case with the Beta project. The *Big data analytics strategy* domain guides the participants to evaluate strategic aspects of data analytics at the organisational level, involving infrastructure concerns, technology goals and governance.

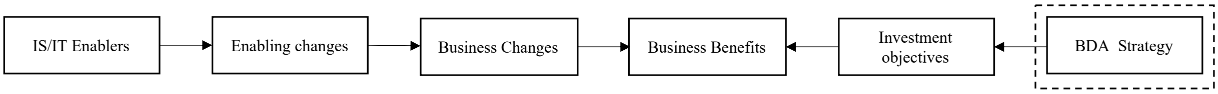

Figure 4: Modified network domains after iteration 1

4.2.2 Iteration 2

In the second iteration, we applied the modified method to the Alpha and Beta projects again within three weeks after iteration 1. Since the first iteration, both project teams had used the content developed in the benefits dependency network actively in the project work. Especially the Beta project had used the *Big data analytics strategy* to steer the project's joint vision. The lack of a joint strategic vision had previously caused tension between the different participants in the first iteration. As we began the second iteration, it was clear how the new *BDA strategy* domain supported both the Alpha and Beta participants in justifying the benefits to support an organisational or departmental vision for big data analytics projects. The project teams could now steer the projects to achieve the strategic vision and guide their development actions accordingly. The dependencies through the domains *Investment objectives*, *Benefits, Business changes* and *Enabling changes* became clearer from having the *BDA Strategy*. We also found the *IS/IT Enablers* domain to cause issues for the participants. They had no issue identifying the needed technology, but it became difficult to move from the *Enabling Change* domain to the *IS/IT enablers* domain, as they tended to focus on the back-end technology of the analytics projects. As noted by a technical lead:
"For sure, it is the change domains that are extremely important in our case, as we have tended to jump directly from investment objectives to defining the technology needed in the IS/IT enablers domain." (Technical lead, Alpha project)

The participants' evaluation further showed that it became less explicit how the analytics results should be provided to the users. It was difficult for the participants to identify the *Business changes and Enabling changes,* as they were uncertain about which work processes, existing systems and technologies they were changing with the project. We needed to develop the *IS/IT enabler* domain of analytics projects and ease the transition between the domains to bridge the technology and the organizational changes. Thus, we split the *IS/IT Enabler* domain into a *Data provider* domain and *Data Analytics* domain (see figures 5). The *Data provider* domain contains the data technology of big data analytics such as data type, integration, load practices, data cleaning, configuration and storage. The *Data analytics* domain contains the type of analytics to be performed and how – a well as where it should be provided to the users. The split into these two new domains supported the participants to evaluate which organisational practices the analytics should support.

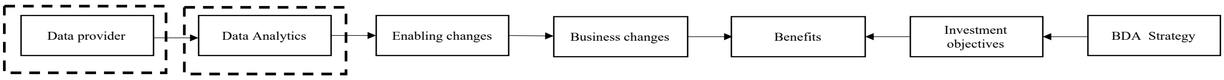

Figure 5: Modified network domains in the method after iteration 2

4.2.3 Iteration 3

In iteration three, we applied the modified method (see figure 5) in the Alpha project, which included participants among senior data scientists, project lead, technical project leads and internal customers. As the Alpha project participated in the two previous iterations, the project team members were familiar with how to work with the benefits dependency network. Thus, the Alpha team required little facilitation in the workshop and managed to create coherence in the content across the domains. In iteration three, we introduced the method with the new network domains depicted in figure 4 to the Gamma project. As the Gamma project participants were not previously familiar with the method, the researchers facilitated the workshop more firmly to ensure that the team members did not skip ahead in any of the domains. Prior to the introduction of the method, the analytics projects tended to first focus on the technical aspects. In the first iterations, we saw how this was the case as well, and thus knew the importance of not letting the project team skip to the *Data provider* and *Data analytics* domain. By the end of the workshop with Gamma, we asked the participants to evaluate the method. This evaluation showed that the project team easily could formulate the content for each of the domains and identify dependencies between–these. The first domain *Big data analytics Strategy* ensured the analytics project would consider the organization's overall big data analytics strategy to avoid working in a silo. From here, the project teams defined the objectives of the analytics project, which led to the benefits down through the organizational change and finally to the technology domains *Data Analytics* and *Data provider.*

From applying the method, the participants managed to create a coherent network. The networks' content was useful for the project teams in operating at different organisational levels from *Big data analytics strategy* through project level benefits and technology. The project team could also extract the benefits dependency networks content and apply it to the documentation they needed to make as part of Vestas' general stage-gate project model. On a negative side, the project teams would place some of the technical development needed outside their projects' scope, which had a clear impact on benefits. Based on our evaluation with the participants, we added a new domain in the benefits dependency network named *Outside enablers* (see figure 6) including the dependent technologies or projects. Essentially this domain describes the risk of not delivering on benefits dependent on factors outside of the project's mandate. As data for big data analytics is generated from multiple sources and technologies to these acquired from different parts of the organisation, we needed to tie these links to create a fuller benefits dependency network.

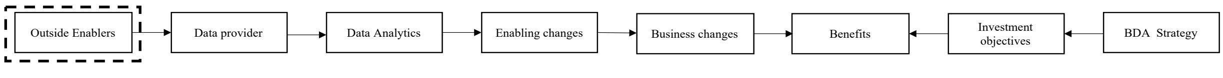

Figure 6: Modified network domains of the method after iteration 3

4.2.4 Iteration 4

In iteration four, we applied the modified method, including content to the *Outside enablers* domain with the project teams in the Alpha and Gamma projects. We conducted two separate workshops in which each of the projects continued the work in the benefits dependency network. After the workshops, the Alpha and Gamma projects now had a full network containing the eight domains, as depict-

ed in figure 6. Through the workshops, the Alpha and Gamma project teams each found a common understanding of the projects despite coming from different background in the organisation:
"*During the final workshop, I experienced how the (benefits dependency) framework facilitated clarification of the different needs from the various stakeholders in the project. It supported us in speaking about expectations despite our different backgrounds"* (Project customer, Gamma project)

In our evaluation with the participants, both of the teams stated the benefits dependency networks content was useful for them to apply in the documentation they needed to develop their projects. A senior data scientist from the Gamma project described his experience after completing the network:
"With this method, you can almost get an epiphany experience, when you see the full picture of the content and the dependencies between all the elements of it." (Senior Data Scientist, Gamma project)

However, we also discovered that for the benefits dependency network to be an important contributor in a project team workshop, it must move beyond being a static tool assembled in a one time off workshop. It must continuously reflect what benefits the project promises to deliver, which means that the project team must revisit the network. Although analytics projects tend to have a shorter duration than other projects – such as developing a new blade design for wind turbines, larger analytics projects may still be years in development. Throughout the project's development stages, the scope may change, and this must be reflected in the benefits dependency network to ensure that the analytics project outcome will be suitable for the project beneficiaries. Thus, through our evaluation, we found that the method must be incorporated into existing project governance practices in an organisation, whether from agile development or stage-gate project development methodologies. The benefits dependency network must be in development, together with the project team. It reflects commitments among the team members and what benefits they expected to deliver at a given time of the project to a given cost. Thus, it assembles a form of project contract that the project team signs off. Furthermore, to follow up on benefits realization after project closure, the benefits must be timely and reflect the benefits recipient's needs upon project completion.

4.2.5 Closing

The resulting problem-solving methodology includes eight instead of five domains compared to the benefits dependency network stemming from IS/IT projects (see figure 1 and 6). Through the iterations in Vestas, we saw how the eight domains contributed positively to creating a coherent network for the analytics projects. Also, the content of the network proved useful for the project teams documentation for management gate approval. The AR study came to a closure when Vestas officially adopted the benefits dependency network methodology. As such, the practical implications of the extended network domains, as depicted in figure 6, provided a significant improvement of big data analytics in Vestas. The department management responsible for the Alpha and Gamma projects adopted the method as part of their project approval gate process and made it a mandatory part of their development projects' feasibility phase in explicating benefits in each of the projects. Thus, a project team must conduct the benefits dependency network tailored to analytics projects with relevant stakeholders from different parts of the organisation before the project could pass gate approval. A strong statement for Vestas, as from each project in which they applied the new methodology, they gained more experience and knowledge on developing the network, and as it became acknowledged at a high level:
"If you compare the projects in which we did not apply the benefits dependency network to those in which we did, then it's quite obvious how the latter projects have a much better end-to-end value chain perspective by bridging the technology to the organisation and benefits" (Senior Vice President)

Vestas decided to integrate the method. As described in the study's initiation phase, together with Vestas, we wanted to develop a method fit for analytics projects and accessible for practitioners. The director of data science specialists in Vestas confirmed and emphasised how the method fits well with the personality types of data scientists:

"It's a strong tool for the very technical analytical minded people you typically have in data science projects. You provide them with a tool that requires them to think out of their comfort zone, but in a logical way". (Director Data science specialists)

We closed the AR study as we, together with Vestas, had developed a method useful for benefits realization in big data analytics projects.

5 Discussion

In the following, we relate the findings from the AR study to our research question: "How can we improve the realization of benefits in BDA projects? Together with Vestas, we developed a methodology to improve benefits realization in big data analytics projects based on previous research (Doherty, Ashurst and Peppard, 2012; Ward and Daniel, 2012; Radford et al., 2014). At the outset of the AR study, Vestas was unsatisfied with their benefits realization from big data analytics projects. Their data analytics project methodology did not consider benefits realization after project closure, and the methodology did not match their need to incorporate a benefits focus and bridge technology to benefits. Alleviating the situation was not simply a question of using existing big data analytics project methodologies (cf. section 2). We needed a new perspective in big data analytics projects and looked into benefits realization management (Doherty et al., 2012; Ward and Daniel, 2012; Radford et al., 2014). Furthermore, we wanted to ensure that the benefits management methodology would be useful for practitioners in a big data analytics setting for Vestas. We refined the benefits dependency network methodology to fit big data analytics projects through iterative applications in Vestas. By evaluating and developing this methodology with Vestas, we ended up with a useful method that Vestas could integrate into already established project development practices. As depicted in figure 6, the method for analytics projects now includes 8 domains.

Benefits Dependency Network for Analytics is what our inquiries into the benefits realization methodology led us to develop through our engagement with Vestas. We reform the benefits dependency network methodology originally developed by Ward et al. (2012) for an IS/IT setting. From iteration 1 (cf. section 4.2.1), we found that the original benefits dependency network domains did not support the big data analytics projects' particularities. However, we confirm and support the point made by (Ward and Daniel, 2012; Radford et al., 2014) that the benefits dependency network serves as a powerful tool in bridging the technology to benefits. To create a coherent network in analytics projects, we needed additional domains in the network. We thus contribute to research on value creation from big data analytics projects with the benefits dependency network. Previous research on benefits management has not considered analytics projects in particular, and we contribute with the new domains; *Outside enablers, Data provider, Data analytics* and *BDA Strategy.* In addition, the domains specific for analytics projects support (Lycett, 2013) claiming that we must combine an inductive and deductive approach in analytics projects. If an organisation solely uses an inductive approach, it neglects the focus on benefits and the value concern for big data analytics projects (Tamm et al., 2013; Gao et al., 2015). The benefits dependency network depicted in figure 6, combines the inductive and deductive approach by linking the *Data provider, Data analytics* and *Benefits* domains.

Incorporation into existing project development practices is essential for the benefits dependency network to be useful. Among the three methodological themes (cf. section 2.2) 1) Agile principles, 2) Business intelligence methods and 3) Data mining development principles, each has pros and cons, which may lead an organisation to prefer one methodology compared to another (Sfaxi and Ben Aissa, 2020). For Vestas, the easy incorporation into existing project development practices was crucial for the success of the benefits dependency network method. An organisation like Vestas does not solely work with data analytics projects; it also produces wind turbines, develops traditional IT and has other types of research and development projects that rely on different methodologies. These projects may depend upon each other for the project outcome, such that a project following a stage-gate methodology can have tasks developed in a project following agile principles. Our research on project development methodologies for big data analytics plug-in to these existing practices. We address the concerns from (Sfaxi and Ben Aissa, 2020) that agile principles for big data analytics projects consider a limited set of users. Our method takes the offset from benefits, involving various users of big data analytics technology. A benefit can be relevant for different users spread throughout the organisation, and thus, the benefits dependency network manages to collect this to the analytics project. As for more classical design methodologies, such as CRISP-DM, our research contributes by incorporating an organisational change and benefits focus, which previously has been neglected (Shearer, 2000).

Facilitation and continuous rework of the benefits dependency network are essential for big data analytics projects. We contribute to the research on benefits management (Ward and Daniel, 2012; Radford et al., 2014) by highlighting the importance of facilitation in building a coherent network. Previous research on benefits management has not explicated how the benefits dependency workshop is facilitated. From our interventions in Vestas (cf. section 4.2), it became clear how the facilitator had a key part in steering the participants through the network domains. The facilitator must ensure that each domain's content is grouped adequately without losing detail granularity while also focusing on the less tangible benefits previously neglected in big data analytics projects (Tamm et al., 2013; Gao et al., 2015). Big data analytics projects require a change in peoples' mindset (Ransbotham, Kiron and Prentice, 2016) to consume the analytical insights and harvest the benefits. Here, our benefits dependency network helps depict how benefits are dependent upon organisational change activities. Moreover, to avoid bias towards one of the network domains, the facilitator must not be a key stakeholder to a specific domain in the benefits dependency network (see figure 6). Instead, it could be a member of the project steering committee or project owner not involved with the project's daily work. Finally, the facilitator must ensure that the participants do not modify the benefits dependency network domains as depicted in figure 6 to avoid the risk of weakening the definitions of the concepts within the network.

6 Conclusion

In this AR study with Vestas, a wind turbine manufacturer relying heavily on big data analytics, we investigated how to improve the realisation of benefits in big data analytics projects. We adopted the benefits dependency network method as our theoretical framework through several iterations with different analytics projects. As a result, we report a benefits dependency network method tailored to analytics projects with big data. Our method fits as a plug-in to existing development practices in an organisation and bridges the orchestration from benefits to technology in these projects. Our findings from Vestas suggests improving the realisation of benefits from big data analytics project by:

1. applying a benefits dependency network tailored for big data analytics projects;
2. incorporating the benefits method into existing project development practices; and
3. developing a workshop facilitation capability for benefits dependency networks.

Our study points to new directions on benefits realisation research in big data analytics projects and how they create business value. Realising benefits from big data analytics projects does not solely come from implementing a big data technology. Thus, future research should address how to place adequate accountability within an organisation to realise big data benefits and verifying benefits and their organisational change activities.

References

Abai, N. H. Z., J. H. Yahaya and A. Deraman. (2013). "User Requirement Analysis in Data Warehouse Design: A Review." *Procedia Technology*, *11*(Iceei), 801–806.

Angée, S., S. I. Lozano-Argel, E. N. Montoya-Munera, J.-D. Ospina-Arango and M. S. Tabares-Betancur. (2018). "Towards an Improved ASUM-DM Process Methodology for Cross-Disciplinary Multi-organization Big Data & Analytics Projects." In: *Communications in Computer and Information Science* (Vol. 877, pp. 613–624).

Baskerville, R. and A. Wood-Harper. (2016). "A critical perspective on action research as a method for information systems research." *Enacting Research Methods in Information Systems: Volume*

2, (1996), 169–190.

Baskerville, R. and A. T. Wood-Harper. (1998). "Diversity in information systems action research methods." *European Journal of Information Systems*, *7*(2), 90–107.

Bholat, D. (2015). "Big Data and central banks." *Big Data and Society*, *2*(1), 1–6.

Blockow, D. (2019). "Agile methodologies for Big Data projects." Retrieved from https://www.d2dcrc.com.au/article-content/agile-methodologies-for-big-data-projects

Checkland, P. and J. Scholes. (1990). *Soft Systems Methodology in Action*. Chichester, West Sussex: John Wiley & Sons Ltd,.

Chen, H., R. H. L. Chiang and V. C. Storey. (2012). "B USINESS I NTELLIGENCE AND A NALYTICS : F ROM B IG D ATA TO B IG I MPACT." *MIS Quarterly*, *36*(4), 1165–1188.

Côrte-real, N., T. Oliveira and P. Ruivo. (2017). "Assessing business value of Big Data Analytics in European firms." *Journal of Business Research*, *70*, 379–390.

Davenport, T. H. and J. G. Harris. (2017). *Competing on Analytics - The New Science of Winning*. Harvard Business School Publishing.

Davison, Martinsons and Ou. (2012). "The Roles of Theory in Canonical Action Research." *MIS Quarterly*, *36*(3), 763–786.

Davison, R. M., M. G. Martinsons and N. Kock. (2004). "Principles of canonical action research." *Information Systems Journal*, *14*, 65–86.

Doherty, N. F., C. Ashurst and J. Peppard. (2012). "Factors affecting the successful realisation of benefits from systems development projects: Findings from three case studies." *Journal of Information Technology, 27(1)*, 1–16.

Dutta, D. and I. Bose. (2015). "Managing a big data project: The case of Ramco cements limited." *International Journal of Production Economics*, *165*, 293–306.

Fernández, J., E. Mayol and J. A. Pastor. (2012). *Agile Approach to Business Intelligence as a Way to Success*. *Business Intelligence and Agile Methodologies for Knowledge-Based Organizations: Cross-Disciplinary Applications*.

Gandomi, A. and M. Haider. (2015). "Big data concepts, methods, and analytics." *Journal of Information Management*, *35*(2), 137–144.

Gao, J., A. Koronios and S. Selle. (2015). "Towards a process view on critical success factors in Big Data analytics projects." *2015 Americas Conference on Information Systems, AMCIS 2015*, 1–14.

Goes, P. . (2014). "Editor's Comments: Big Data and IS Research." *MIS Quarterly*, *38:3*, iii–viii.

Grady, N. W., J. A. Payne and H. Parker. (2017). "Agile Big Data Analytics." *2017 Ieee International Conference on Big Data (Big Data)*, 2331–2339.

Günther, W. A., M. H. Rezazade Mehrizi, M. Huysman and F. Feldberg. (2017). "Debating big data: A literature review on realizing value from big data." *Journal of Strategic Information Systems*, *26*(3), 191–209.

Iversen, Mathiassen and Nielsen. (2004). "Managing Risk in Software Process Improvement: An Action Research Approach." *MIS Quarterly*, *28*(3), 395.

Jensen, M. H., P. A. Nielsen and J. S. Persson. (2019). "Managing big data analytics projects: The challenges of realizing value." *27th European Conference on Information Systems - Information Systems for a Sharing Society, ECIS 2019*, (June).

Larson, D. and V. Chang. (2016). "A review and future direction of agile, business intelligence, analytics and data science." *International Journal of Information Management*, *36*(5), 700–710.

Lindberg, A. (2020). "Developing theory through integrating human and machine pattern recognition." *Journal of the Association for Information Systems*, *21*(1), 90–116.

Locke, K., K. Golden-Biddle and M. S. Feldman. (2008). "Making doubt generative: Rethinking the role of doubt in the research process.” *Organization Science*, *19*(6), 907–918.

Loebbecke, C. and A. Picot. (2015). “Reflections on societal and business model transformation arising from digitization and big data analytics: A research agenda.” *Journal of Strategic Information Systems*, *24*(3), 149–157.

Lycett, M. (2013). ““Datafication”: Making sense of (big) data in a complex world.” *European Journal of Information Systems*, *22*(4), 381–386.

Marchand, D. A. and J. Peppard. (2013). “Why IT Fumbles Analytics.” *Hardward Busines Review*, *January-Fe*, 112.

Marshall, A., S. Mueck and R. Shockley. (2015). “How leading organizations use big data and analytics to innovate.” *Strategy & Leadership*, *43*(5), 32–39.

Mathiassen, L. (2002). “Collaborative practice research.” *Information Technology & People*, *15*(4), 321–345.

McKay, J. and P. Marshall. (2001). “The dual imperatives of action research.” *Information Technology & People*, *14*(1), 46–59.

Mikalef, P. and M. Gupta. (2021). “Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance.” *Information and Management*, *58*(3), 103434.

Mikalef, P., I. O. Pappas, J. Krogstie and P. A. Pavlou. (2020). “Big data and business analytics: A research agenda for realizing business value.” *Information and Management*, *57*(1).

Mithas, S., M. R. Lee, S. Earley, S. Murugesan and R. Djavanshir. (2013). “Leveraging big data and business analytics.” *IT Professional*, *15*(6), 18–20.

Nielsen, P. A. and J. S. Persson. (2016). “Engaged Problem Formulation in IS Research.” *Communications of the Association for Information Systems (CAIS)*, *38*(35), 720–737.

Paavola, S. (2004). “Abduction as a Logic and Methodology of Discovery: the Importance of Strategies.” *Foundations of Science*, *9*(3), 267–283.

Provost, F. and T. Fawcett. (2013). “Data Science and its Relationship to Big Data and Data-Driven Decision Making.” *Big Data*, *1*(1), 51–59.

Radford, S. A., P. Panuwet, R. E. Hunter, D. B. Barr and P. B. Ryan. (2014). “HPLC-MS/MS method for the measurement of insecticide degradates in baby food.” *Journal of Agricultural and Food Chemistry*, *62*(29), 7085–7091.

Ransbotham, B. S., D. Kiron and P. K. Prentice. (2016). “Beyond the Hype : The Hard Work Behind Analytics Success is declining and what to do about it.” *MIT Sloan Management Review*, (57381), 19.

Romero, O. and A. Abelló. (2009). “A Survey of Multidimensional Modeling Methodologies.” *International Journal of Data Warehousing and Mining (IJDWM)*, *5*(2), 1–23.

Sfaxi, L. and M. M. Ben Aissa. (2020). “DECIDE: An Agile event-and-data driven design methodology for decisional Big Data projects.” *Data and Knowledge Engineering*, (September), 101862.

Shearer, C. (2000). “The CRISP-DM model: The new blueprint for data mining.” *Journal of Data Warehousing*, *5*(4), 13–22.

Shollo, A. and R. D. Galliers. (2016). “Towards an understanding of the role of business intelligence systems in organisational knowing.” *Information Systems Journal*, *26*(4), 339–367.

Sivarajah, U., M. M. Kamal, Z. Irani and V. Weerakkody. (2017). “Critical analysis of Big Data challenges and analytical methods.” *Journal of Business Research*, *70*, 263–286.

Sun, J., W. Xu, J. Ma and J. Sun. (2015). “Leverage RAF to find domain experts on research social network services: A big data analytics methodology with MapReduce framework.” *International Journal of Production Economics*, *165*, 185–193.

Svejvig, P. and B. R. Schlichter. (2020). “Resources, capabilities and public value creation in a healthcare IT project: an action research study." *International Journal of Managing Projects in Business*, *14*(1), 1–19.

Tamm, T., P. Seddon and G. Shanks. (2013). "Pathways to value from business analytics." *International Conference on Information Systems (ICIS 2013): Reshaping Society Through Information Systems Design*, *4*, 2915–2930.

Tardio, R., A. Mate and J. Trujillo. (2015). "An iterative methodology for big data management, analysis and visualization." *Proceedings - 2015 IEEE International Conference on Big Data, IEEE Big Data 2015*, 545–550.

Ward, J. and E. Daniel. (2012). *Benefits Management*. John Wiley & Sons Ltd,.

White, S. K. (2015). "Study reveals that most companies are failing at big data." Retrieved from https://www.cio.com/article/3003538/study-reveals-that-most-companies-are-failing-at-big-data.html