Scandinavian Journal of Information Systems

Volume 35 | Issue 1 Article 2

6-30-2023

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© Scandinavian Journal of Information Systems, 2023 35(1), 41-78

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Abstract. Big data analytics is the next frontier in creating digital opportunities for businesses. However, analytics projects rarely deliver the intended benefits for the organizations that invest in these. To address this challenge, we report from an action research study on improving benefits realization in Vestas, an organization highly involved with big data analytics. Here, we introduce the benefits dependency network, a map of the relationships between analytics technology, organizational change activities, stakeholders' interests, and the potential benefits of a big data analytics project. Through four action research iterations involving three projects in Vestas, we developed and evaluated a method for benefits dependency networks for big data analytics. In this study, we present lessons on: (1) the usefulness of the method in big data analytics projects, (2) how it can be embedded into existing project methodologies, and (3) how facilitation is needed in connecting the domains supporting benefits realization needs. We conclude the paper by discussing our lessons' contributions to the extant research on big data analytics and benefits realization management.

Key words: big data analytics, benefits management, benefits dependency network, action research.

Accepting editor: Henri Pirkkalainen

1 Introduction

Big data analytics draws attention from academic and practitioner communities, which describe it as the next frontier for innovation (Gandomi & Haider, 2015; Günther et al., 2017; Marshall et al., 2015). Many large organizations have already adopted big data analytics or begun to do so, but even though it can be a valuable intangible asset, its adoption poses serious challenges (Tardio et al., 2015). Essentially, the adoption of what big data analytics delivers to the organization, is crucial for the organization to realize any value from its investment in big data analytics projects. In this relation, the challenge of extracting value from massive volumes of data has been considered paramount to understanding the dynamics and social environments of an organization (Loebbecke & Picot, 2015). Further, academic research on big data analytics' impact on an organization's performance is still in its infancy (Raguseo, 2018). According to a worldwide survey conducted by PwC in 2015, 43% of organizations obtain little or no benefit from big data analytics (White, 2015), and organizations in general struggle with achieving a strategic advantage from the big data analytics initiatives (Côrte-Real et al., 2019).

Several scholars and practitioners have been trying to understand and unpick the link between deploying big data analytics and how an organization achieves a competitive advantage from it (Constantiou & Kallinikos, 2015; Danielsen et al., 2021; George et al., 2014). As a research field, progress have been made at especially 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 (Danielsen et al., 2021; Mikalef et al., 2020a; Mikalef et al., 2021). However, there is still a limited understanding of how value is generated from big data analytics projects and the dynamics in these going beyond technical considerations (Hughes & Ball, 2020). Much research based on case studies tend to focus on the technologies concerning big data analytics (Conboy et al., 2020; Fosso Wamba et al., 2015). Yet, an understanding of how an organization can overcome the challenges associated with realizing value at the big data analytics project level is still scarce (Chiang et al., 2018; Hindle et al., 2020). A big data analytics project can involve both soft and hard benefits as equally important for the project's success. Examples of soft benefits include user satisfaction and trust in analytical results, whereas hard benefits involve decreases in cost measures and efficiency gains. In this study we adopt the term benefit as this entails both the soft and hard contributions from a big data analytics project.

We contribute to the calls for research of how exactly organizations can obtain value from big data analytic projects. We do so from real-life projects in an organization heavily involved with such practices, Vestas Wind Systems A/S (Vestas). We adopt an action research methodology (Mathiassen, 2002; Mckay & Marshall, 2001), as it affords investigation of organizational processes, such as big data analytics value creation, with a particular focus on how practitioners can and should take action. We address the research concern for the empirically based synthesis of big data analytics value research applying benefits realization management as our theoretical lens. Specifically we present contributions on how value can be obtained from big data analytics projects through benefits realization management practices evolved from IS/IT project benefits realization (Ward & Daniel, 2012). In this study, we collaborated with a group of practitioners engaged in big data analytics projects, which led to joint knowledge interest in the following research question: *How can we improve the realization of benefits in big data analytics projects*?

The use of *we* emphasize the collaborative nature of action research involving both we as researchers but also the practitioners. The verb *improve* then refers to the change constituted by the action research process as a core principles in both benefitting practice and contributing to research (Mckay & Marshall, 2001). Thus, in contrast to the formerly mentioned research based on case studies, we as researchers in this study collaborated with practitioners on making changes that improve the realization of benefits at a big data analytics project level.

In the following, 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 action research activities in Vestas to show how a benefits management focus on big data analytics projects helps obtain benefits for the organization and serves as a means of orchestration between big data technology, organizational change activities, and stakeholder interests.

2 Related research

Big data analytics is characterized by huge volumes of numerous observational data used in a decision-making process (Goes, 2014) and is typically described in terms of the three Vs of volume, velocity, and variety (Philip Chen & Zhang, 2014). Some researchers define big data analytics as the procedure of accumulating, consolidating, scrutinizing, and exploiting large sets of data from autonomous and heterogeneous resources to improve managerial decision making (Sun et al., 2015). A key aspect of these definitions is that, in the end, they are about decision-making. Whether from AI in an automated form or embedded in people's daily work in organizations, big data analytics must produce actionable intelligence to create value (Davenport & Harris, 2017).

2.1 Challenges and benefits of Big Data Analytics projects

Big data analytics is no longer siloed within one specific department that collects, analyses, and exposes the data to decision makers but instead spread throughout the organization (Sheng et al., 2017; Sivarajah et al., 2017). The challenges for realizing benefits from big data analytics are many (Jensen et al., 2019). As example explicating benefits and defining measures to these from the project level, is a struggle, however a central activity for an organization in order to realize benefits from these (Jensen et al., 2019). Moving from the project level, recent studies on big data analytics acknowledge that an organization must develop a firm-wide capability to leverage big data analytics to realize value (Mikalef et al., 2020b). 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 (Lumor et al., 2021; Mikalef et al., 2020b; Viaene and Van Den Bunder, 2011)although research and practice have advanced the technical aspects of big data, comparable advancements in the social aspects (i.e., human and structural aspects. As example, Lumor et al., (2021) address value creation from the socio-technical perspective and present a set of heuristics that can guide, specifically, healthcare institutions in how to establish the socio-technical context to benefit from big data analytics. They call for research that bridges the technical and social aspects of realizing benefits from big data analytics.

The procedure through which big data analytics is transformed into actionable intelligence is difficult (Sivarajah et al., 2017) and involves organizations investing in big data analytics projects. However, these projects are often complex, high-risk, and they demand cross-departmental collaboration in an organization that also involves actors with various skills (Maritz et al., 2020; Mikalef & Gupta, 2021; Sfaxi & Ben Aissa, 2020). Moreover, big data analytics projects are often compared to well-defined scientific experiments or clinical trials and have a shorter duration compared to traditional IT projects (Marchand & Peppard, 2013). As organizations continue to invest in big data analytics projects, we see two main kinds of challenges that has emerged: the first is related to technology, and the second is related to big data analytics semantics (Günther et al., 2017). For the first challenge, we know that these projects use data from various sources. Data such as transactional data from enterprise resource planning systems to external data that can be user-generated, sensor data, and third-party data add to the complexity of creating benefits from big data analytics projects. Thus, big data analytics projects have to overcome the technical challenges of managing these types of data, their variety, and the speed in which they are generated (Günther et al., 2017). For the second challenge, once an organization has succeeded with its big data analytics technology efforts, it must then look into the semantics of finding and meaningfully combining the data, turning them into information, and providing decision support (Dutta & Bose, 2015). In addition, depending on the granularity and variety of the data included, the big data analytics project team may work to design which insights can be elicited ex-ante (Günther et al., 2017).

Inductive, deductive, and abductive approaches to big data analytics are concerned with information discovery from big data (Lindberg, 2020; Lycett, 2013). The inductive approach begins with data and then discover previously unknown patterns (Shollo & Galliers, 2016). This makes benefits difficult to identify (Gao et al., 2015; Tamm et al., 2013). The deductive approach begins with a theory and then uses data to test it, and it may be key to identifying benefits and how they may be realized (Bholat, 2015). It has been suggested that the inductive must be combined with the deductive and thus resembling an abductive approach in which the data will be utilized in gaining a better understanding of observations through testing and theory application (Lindberg, 2020; Locke et al., 2008; Paavola, 2004).

Projects on data analytics tend to rely on general approaches that are tailored to other types of projects and are typically managed with one of three approaches (Sfaxi & Ben Aissa, 2020):

- Agile approaches: are iterative and incremental, seems to fit well with the development environment for data analytics (Larson & Chang, 2016), and used by many (Blockow, 2019; Fernández et al., 2012). One approach for data analytics projects contains several steps mixing a bottom-up approach with a business vision (Sfaxi & Ben Aissa, 2020). While a vision is necessary it is insufficient as a statement of benefits let alone benefits realization.

- Business intelligence approaches: have been somewhat adapted to big data analytics projects (Abai et al., 2013; Romero & Abelló, 2009). These approaches typically apply to classical business intelligence applications that obtain data from a stable and static source where the data warehouse is centralized and structured with periodic extract, transform, and load. Yet, big data analytics projects contain data sources that may be unstructured and generated with high velocity. However, classical business intelligence development approaches provide a poor fit for data big data analytics projects (Provost & Fawcett, 2013).

- Data mining approaches: more classic approaches such as CRISP-DM, KDD, Analytics Canvas, and SEMMA (Angée et al., 2018; Kühn et al., 2018). These approaches seek to discover and understand data to utilize adequate mining models. However, these approaches tend to deal quite swiftly with the organizational and benefits aspects of big data analytics projects (Shearer, 2000). For example, the CRISP-DM guide provides little or no guidance as to how to measure benefits and support changes in the organization for analytics deployment.

The three types of existing approaches do not substantiate a benefit focus in big data analytics. This is why we look to research on IS/IT projects' benefits realization to improve the benefits orientation for big data analytics projects.

2.2 Benefits realization management and benefits dependency networks

A benefits management approach from IS/IT projects (Peppard, Ward & Daniel, 2007; Ward & Daniel, 2012) could potentially substantiate a benefits focus in big data analytics projects . Traditional project and investment approaches force IT project managers to overstate benefits and not define them accurately in an organizational setting. Instead, the benefits management approach focuses on accurately identifying benefits and planning to realize them. Ward and Daniel (2012) described the approach as "the process of organizing and managing so that the potential benefits from IT are actually realized" (p. 8). A central approach for benefits management is to develop the *benefits dependency network*, which supports the bridging of benefits for users and business managers to technology stakeholders. The benefits dependency approach's core feature is identifying expected benefits and how these benefits will be realized from an IT project (Daniel, Peppard & Ward, 2007). Moreover, the benefits dependency network creates a link between IT/IS enablers and business objectives to include both indirect, delayed, and intangible benefits (Jenner, 2012; Ward & Daniel, 2012).

The benefits dependency network framework has been applied in different fields such as customer relationship management, software development and also, big data analytics (Jabbari et al., 2018; Maritz et al., 2020). The framework has been used to either synthesizes or analyze some data. For example, Maritz et al. (2020) used it as a theoretical framework to elicit implementation issues for big data analytics from the literature. They highlight the framework's ability to consider the relationship between people, process, and technology that may assist managers in understanding how benefits are expected to be delivered. While Maritz et al. (2020) use it to structure a literature review we seek to use it in actual project with practitioners.

The benefits dependency network 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, links benefits to technology, and hence provides a key overview to the project participants involved. The approach seeks to ensure that the business demand for technology development is rooted in the benefits that the business will receive.

As the benefits dependency network helps link the overall investment objectives and the requisite benefits with the necessary business changes, it becomes an essential approach for a project team to create a plan for delivering the identified benefits. A benefits dependency network consists of five categories that link IT/IS enablers to a project's overall investment objectives, see Figure 1. The approach suggests that the network should be constructed over a series of workshops involving stakeholders relevant to each of the categories.

Figure 1. Benefits dependency network categories (Ward and Daniel 2012).

The approach further suggests that 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 business-demand rather than IT supply. 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 innovation-based investments often require evaluating some technologies that, at first, do not explicitly state their objectives or benefits (Daniel et al., 2007) most organizations focus on implementing the technology rather than on realizing the expected business benefits. Consequently, benefits are not forthcoming, despite a project's technical success. Drawing on more than 10 years of research studying how organizations can improve the return on their IT investments, we present an approach for identifying, planning, and managing the delivery of benefits. Our benefits management approach begins with IT professionals and business managers together answering seven questions about a potential IT investment. These questions aim to uncover three important aspects of the investment: the ends (the target performance improvements.

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). Therefore, the category Enabling changes includes 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 the measures and roles responsible for each benefit. Hereafter, changes can be assigned to the right person, and timescales can also be established. 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 & Daniel, 2012). As such, benefit management may substantiate the value perspective of projects.

3 Research method

In bridging benefits management, and specifically the benefits dependency network, with big data analytics projects, we engaged in action research to address the research question and the need of the client organization, Vestas. Action research is appropriate, as our research question addresses how practitioners take action and improve these actions, e.g., how to improve the realization of benefits (Baskerville & Wood-Harper, 1998, 2016; Davison, 2004; McKay & Marshall, 2001). We addressed the research question in Vestas, which is a Danish wind-turbine manufacturer with more than 25,000 employees worldwide, accounting for more than 20% of all wind power capacity globally. Vestas uses big data in various ways to improve the performance of wind turbines and for decision-making in the organization, deploying both predictive and prescriptive big data analytics. The organization is highly experienced in big data and analytics technologies, but it lacks a benefit focus in its big data projects. Thus, the big data analytics projects in Vestas are appropriate units of analysis for our research.

3.1 The Action Research approach

Action research links theory and practice in a cyclic process with the intention of creating a synthesis of specific knowledge, providing actors in the situation with the capability to act and with general knowledge useful in similar situations, (Baskerville & Wood-Harper, 2016). Action research is appropriate and highly relevant to situations in which improvement is needed. It requires that the improvement of a problematic situation is a targeted intervention (Mckay & Marshall, 2001). The targeted intervention must be based on an in-depth understanding of both the theoretical and real-world context in which the problem takes place (Nielsen & Persson, 2016). Our research design was based specifically on collaborative practice research (Mathiassen, 2002). Collaborative action research is iterative, involving one or more cycles of activities focusing on change through collaborative interventions in an organizational context. Figure 2 is a cyclical process that operationalizes collaborative action research between the researchers and the practitioners at Vestas.

3.2 The research context

Since its investment in the world's third-largest commercial supercomputer Firestorm in 2013, Vestas has responded and expanded rapidly to the rising demand for the digitalization of the renewable energy sector. Big data analytics is increasingly integrated into the organization, embedding enormous volumes of data into daily operations. In terms of the three Vs typically applied to describe big data, *volume* is given by the amount of data points that Vestas has stored since 2000. Here, time-series data (hour by hour) of more than 50,000 turbines has been accumulated from sensors distributed within a turbine. As the number of turbines expands, the volume of data stored continuously increases. The *velocity* of big data in Vestas (for example, one specific turbine) can easily generate and transmit over 200 gigabytes of data per day. Finally, in terms of *variety*, Vestas applies several types of data to its big data analytics projects that are generated both internally and externally. Examples of these data include cost of service, wind resource data (based on more than 200 parameters), service data, turbulence, height contours at the turbine site, site pictures, flow over terrain data, and much more. Essentially, big data is evident within Vestas, and the organization has deep knowledge in working with big data. However, the organization still faces major challenges in its big data analytics efforts. In answering the main research question of this paper, we report from three different big data analytics projects in Vestas. The projects were selected based on their application of big data analytics and their different project approaches.

Each of the projects allowed the researchers to access the project information and to make interventions throughout the lifetime of the project. The projects could both illuminate the main research question and moreover had a strategic importance for Vestas in enhancing the organizations competitive advantage by applying big data analytics in different forms. In the following, each of the projects are presented.

First, the *Alpha* project was complex in its setup, as it involved multiple sources of data that were rooted both outside and inside Vestas. As example, data outside of Vestas included exchange rate data, labour cost, import tax and raw material cost. Data inside Vestas, as example, included the power curve models for the different types of turbines, loads data and service cost. The project aimed to combine the aforementioned examples of data and many more data sources to provide analytical insights to senior managers in deciding upon product roadmaps 5 and 10 years into the future. The output of the project was an analytical tool that could be used continuously to inductively analyze the data to establish the most optimal product configurations to place for development in product roadmaps. The project included advanced statistics combining actual and predictive performance data, cost data for manufacturing turbines, and market data. The overall project was jointly developed with another project in Vestas that followed a stage-gate development process.

Second, the *Beta* project was based in the service department, with the objective of enhancing the service applications used by wind turbine service technicians across the globe. This objective was to be achieved by integrating established business intelligence applications and combining the analytics results to support the service technicians in their daily work. This project combined service applications with predictive monitoring of potential turbine errors based on advanced analytics of the turbines' actual performance, component failure, and energy production. The overall project followed agile development practices, which had previously been adopted as standard process in the service department.

The final project, *Gamma*, had the objective of enhancing the value offered by the wind turbine power plant concerning the amount of energy the plant produces, the certainty of production predictions, and the load 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. Based on Vestas' unique global climate library, the project potentially works on data from more than 38,000 turbines online in the system and historical data from more than 61,000 turbines and 10,000 meteorological masts. It includes hour-by-hour production data and more than 100 climate variables to apply for analysis with a big data solution that reduces the geographic grid area by 90% to increase accuracy in estimating a potential power plant. The overall project had to conform to a stage-gate project process applied in Vestas for projects of a certain size in terms of assigned resources and development hours. However, as the project moved into the development phase in developing the big data analytics solution, it was allowed to follow agile development practices. In the information discovery phase, the *Gamma* project adopted an abductive approach in analyzing how to optimize a power plant's lifetime management based on what was already known about the power plant. For example, this was done in terms of loads and turbine type, and external customer data that however could change the initial computed proposal of how to optimize the power plant.

3.3 Research design

The problem situation was collaboratively formulated between the researchers and practitioners at Vestas. In our study we combined theory and practice as follows:

- Research theme: The area of concern (A) was benefits realization from big data analytics projects. Specifically, within this area of concern the problem (P) and the research question (RQ) was on how to improve the area of concern for Vestas. Section 2 summarized how this A and the RQ had been addressed in extant research.

- Research framework (FA): Theory and concepts about the area of concern, that is, big data analytics value creation and benefits management framed our study. Specifically, we applied the framework of benefit dependency networks stemming from benefits realization management as our initial problem-solving framework. The initial FA was found in the extant research literature as summarized in Section 2.

- Problem-solving methodology (MP): A method that evolved over time with the iterations in Figure 2. The problem-solving is based on FA and then also a process for conducting a workshop to understand and specify benefits for a particular big data analytics project. This eventually also evolved FA and the elements of benefits dependencies.

- Research methodology (MR): Collaborative practice research with particular activities depicted in Figure 2.

In the study's initiation phase, several challenges in Vestas were diagnosed in detail to appreciate the problems faced. 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 one and two hours each.

The iterative steps 4-6 in Figure 2 were refining both the benefits dependency approach and the understanding of how to manage big data analytics value. The iterating activities have a joint purpose for practitioners and researchers to test and further tailor and detail the approach in applying it to various big data analytics projects. The evaluation was in a real-world setting from which real-world problems concerning big data analytics projects.

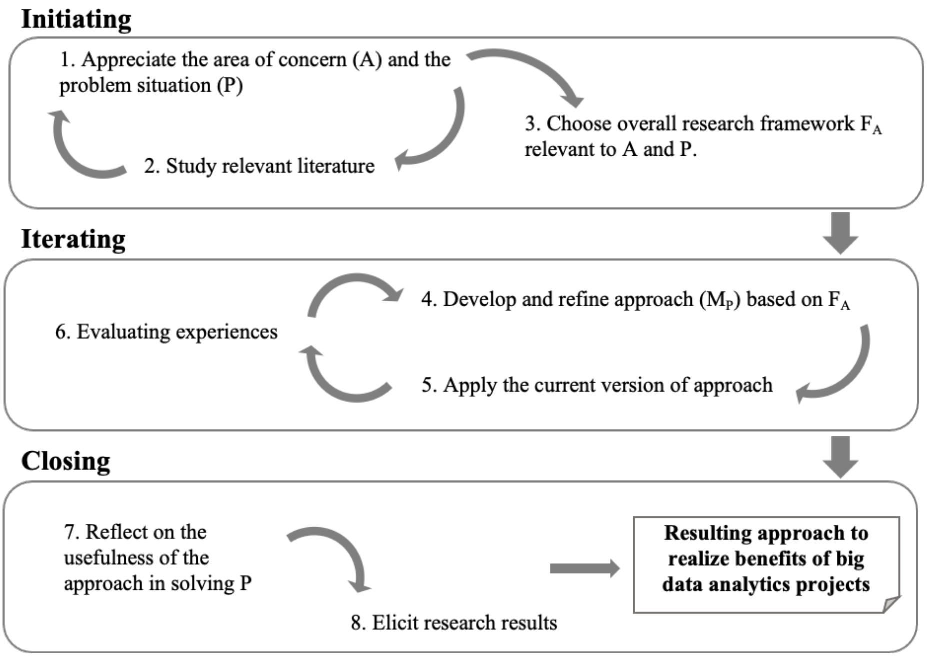

Figure 2. Research design

3.4 Data collection

Considerable effort was spent in collecting data and analyzing the data on to develop the problem-solving method. This effort relates to the collaborative practice research criterion of documentation the action research (Iversen et al. 2004). The data collection process was supported by the insider-researcher role, as one of the authors worked at Vestas with the specific task of conducting action research on benefits realization of big data. She was immersed in the organization prior to the study and obtained a pre-understanding from being an actor in the big data analytics projects and departments reported here. This allowed for gaining access to data at various levels in the organization and in big data analytics projects. The following data collection techniques were used:

- Audio recordings of workshops with researchers and practitioners
- Researchers' individual research diaries
- In-depth qualitative interviews as part of the diagnosis and assessment of usefulness stages
- Big data analytics project documentation and business cases in the client organization
- Participant observations from various meetings in the client organization, such as department meetings and strategy workshops

For each of the big data analytics projects in Vestas, the researchers participated in project status meetings, benefits-realization meetings, and workshops. Participant observation (Myers & Newman, 2007) was practiced in department meetings in which the projects were anchored and served as information at the strategic level. Since the data provided from participant observation were not recorded in the meetings, field notes were taken and the researchers debriefed (Spall, 1998) on a weekly basis to ensure that the information obtained was shared and made available for later analysis. Documentary evidence was obtained from each of the three projects and included in the action research study. The documents included business case justification, design descriptions, stage gate presentations, cost and hour allocation material, and minutes of meetings from steering committee meetings. Together with the iteration activities in Vestas, the data obtained from participant observations and documentary evidence provided in-depth insights into each of the big data analytics projects and their challenges for benefits realization.

3.5 Data analysis

The different types of data obtained was analyzed jointly with each evaluation activity in the action research activities, cf., Figure 2. The collected data was used as a shared point of references between the researchers in substantiating the first author's observations and experiences in Vestas. Essentially the analysis of the data was reflective (Mathiassen & Sandberg, 2013) in the sense that the first author provided the action experience and access to the data at Vestas while the second and third author provided reflective and analytical capabilities that were independent of the traditions and culture at Vestas. The authors combined autonomous and communicative reflectivity (de Vaujany, 2008) to analyze the data obtained. Autonomous reflexivity was based on each of the authors individual reading of the data material and debrief of the workshop iterations, and then developed through communicative reflexivity. Differences in interpretation were then reconciled through discussion. As example, in the research activity Develop in which the researchers would further develop the benefits dependency network based on the interpretations of the research iteration and related data leading up to the activity of developing the network.

4 Research activities

The research activities followed the activities in the research process model (Figure 2) and summarized in Table 1. The researchers were involved with three different analytics projects in Vestas during the intervention: projects *Alpha*, *Beta*, and *Gamma*. The projects involved different stakeholders and departments, but they were all characterized by the need to combine and utilize large amounts of data across various departments in Vestas to extract analytical insights.

<table>
<tr><th>Research activity</th><th>Contents</th><th>Participants</th><th>Hours of collaboration</th></tr>
<tr><td>Initiation</td><td>Analyzing the problem, clarifying challenges, setting the scene, studying relevant literature.</td><td>Data scientists, project managers, head of department, chief specialist, and product managers.</td><td>34</td></tr>
<tr><td>I1: Develop</td><td>Application of benefits dependency framework and approach by Ward and Daniel (2012).</td><td>Researchers.</td><td rowspan="2">4
4</td></tr>
<tr><td>I1: Apply</td><td>Alpha project: Apply approach in workshop.
Beta project: Apply approach in workshop.</td><td rowspan="2">Data scientists, project managers, product managers, project customers, technical leads, and researchers.</td></tr>
<tr><td>I1: Evaluate</td><td>Elicited from participants' statements and autonomous and communicative reflectivity.</td><td>2</td></tr>
<tr><td>I2: Develop</td><td>Extend F_A with a new domain, 'BDA Strategy.'</td><td>Researchers.</td><td>2</td></tr>
<tr><td>I2: Apply</td><td>Alpha project: Apply extended approach in workshop.
Beta project: Apply extended approach in workshop.</td><td rowspan="2">Data scientists, project managers, product managers, project customers, technical leads, and researchers.</td><td>3
3</td></tr>
<tr><td>I2: Evaluate</td><td>Elicited from participants' statements and autonomous and communicative reflectivity.</td><td>2</td></tr>
<tr><td>I3: Develop</td><td>Extended F_A with new domains, 'Data provider' and 'Data Analytics.'</td><td>Researchers.</td><td>2</td></tr>
</table>

Research activity	*Contents*	*Participants*	*Hours of collaboration*
I3: Apply	Alpha project: Apply extended approach in workshop. Gamma project: Apply extended approach in workshop.	Data scientists, project managers, product managers, project customers (internal), technical leads, head of department, and researchers.	3 4
I3: Evaluate	Elicited from participants' statements and autonomous and communicative reflectivity.		2
I4: Develop	Extended F_A with a new domain, 'Outside Enablers' and evolved into M_P	Researchers.	2
I4: Apply	Alpha project: Apply method in workshop. Gamma project: Apply method in workshop.	Data scientists, project managers, product managers, project customers (internal), technical leads, head of department, and researchers.	3 2
I4: Evaluate	Elicited from participants' statements and autonomous and communicative reflectivity.		2
Closing	Incorporation into existing project development practices. Closing interviews with key managers on the effects and usefulness of the resulting method.	Senior data scientist, head of Data and Analytics Department, Vice President for Analytics, project customers, and researchers.	4
Closed	Elicitation of results relevant to research and practice.	Researchers.	2

Table 1. Research activities following the process in Figure

4.1 Initiating

Based on the detailed diagnosis in the study's initiation phase and a joint discussion of the problem, together with relevant stakeholders in Vestas, we identified benefits realization management as a key concern in analytics projects. This led to jointly initiated improvement activities for benefit management in analytics projects. Together with the key stakeholders in Vestas, we considered the issues of: (1) making benefits realization management fit for analytics projects, (2) the need for benefits realization in analytics projects to be accessible for practitioners, and (3) the limited empirical knowledge of value realization in big data analytics projects. We adopted the benefits dependency network approach (Peppard et al., 2007; Ward and Daniel, 2012), as it has been established for IT projects in general and looked promising for analytics projects as well.

4.2 Research iterations

We had a total of four iterations in Vestas, see Table 1. The *Alpha* project continued throughout all four iterations, whereas the *Beta* project followed the first two iterations, and the *Gamma* project followed the last two.

Figure 3. *Alpha* project team workshop.

Iteration 1

In the *Alpha* and *Beta* projects' feasibility phase, where they defined the projects' scope, costs, and value propositions, we applied the benefits dependency approach containing the original five categories (see Figure 1) in two workshops.

We began the *Alpha* project with the workshop, in which members representing each of the benefits dependency network categories were present. At the workshop, the researcher presented the benefits dependency framework and facilitated the team members' work with the categories. 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 category should contain.

We then continued with the *Beta* project in a separate workshop. The *Beta* project consisted of two separate teams and digital applications that had now been integrated. Through this integration of analytical systems, users are to be better informed in their decision-making processes and use only 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 have a shared vision of the project at the outset of the workshop. This lack of a shared vision created conflicting intentions about the *Beta* project's objectives and benefits.

Both workshops ended with an evaluation. We found that, in its initial form, the benefits dependency network already had a positive effect on moving the focus from being solely on data and analytics technologies toward benefits. Further that the initial approach structured progressing from benefits to technology. As stated by the senior project manager:

> Building a [benefits] network has enormous appeal, as it is very structured and helps 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 big data analytics projects to guide our current project work.(Technical lead, Alpha project)

The strategic level should guide 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 applications to develop relevant content in the benefits network. During the workshop in *Beta,* the researchers therefore included the strategic vision as a category in the benefits network. It had a

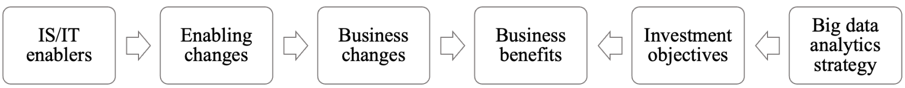

Figure 4. Modified network domains after iteration 1.

clear positive impact on aligning *Beta*'s two teams to being one joint team with a shared strategic vision. Based on this we modified the benefits dependency framework from its initial form (see Figure 1) to include a new domain, *Big data analytics strategy*, to the right (see Figure 4). We also changed the definition in the network elements from that of categories to domains to convey that the benefits dependency network operates at different levels in the organization and across organizational boundaries—as in the *Beta* project. As such, the *Big data analytics strategy* domain guides the participants to evaluate strategic aspects of data analytics at the organizational level, involving infrastructure concerns, technology goals, and governance.

Iteration 2

In the second iteration, we applied the modified approach to the *Alpha* and *Beta* projects again within three weeks after Iteration 1. Since the first iteration, both project teams have actively used the content developed in the benefits dependency network in the project work. In particular, 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 *Big data analytics strategy* domain supported both the *Alpha* and *Beta* participants in justifying the benefits of supporting an organizational 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*.

In this iteration we also found that the *IS/IT enablers* domain caused issues for the participants. They had no issue identifying the needed technology, but it became difficult to move from the *Enabling changes* 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 showed that with the existing domains 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 technology and organizational changes. Thus, we eventually split the *IS/IT Enabler* domain into a *Data provider* and a *Data analytics* domain (see Figure 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 organizational practices the analytics should support.

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

Iteration 3

In Iteration 3, we applied the modified domains (see Figure 5) in the *Alpha* project, which included participants from 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 3, 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 benefits approach, the researchers facilitated the workshop more firmly to ensure that the team members did not skip ahead in any of the domains. The analytics projects tended previously to focus on technical aspects. In the first iterations, we saw this as well, and we thus knew the importance of not letting the project team skip to the *Data provider* and *Data analytics* domains. At the end of the workshop with *Gamma*, we asked the participants to evaluate the approach. This evaluation showed that the project team could easily formulate the content for each of the domains and identify dependencies between them. The first domain, *Big data analytics strategy*, ensured that 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.*

By applying the benefits dependency approach (see Figure 5), the participants managed to create a coherent network. The networks' content was useful for the project teams in operating at different organizational levels, from *Big data analytics strategy* through project level benefits and technology. The project team could also extract the content of the benefits dependency network 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. Therefore, based on our evaluation with the participants, we added a new domain in the benefits dependency network called *Outside enablers* (see Figure 6), which included 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 are generated from multiple sources and technologies to those acquired from different parts of the organization, we needed to tie these links to create a fuller benefits dependency network.

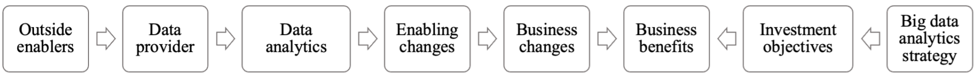

Figure 6. Modified network domains of the method after iteration 3.

At this point we also had come to explain the approach to the participants as a method, MP, as based on workshop techniques with brainstorming on post-it notes, clustering notes, drawing dependencies between network elements, and ensuring consistency in the use of the domains as well as coherence between the domains. We deliberately insisted on building on the dependency network as a framework, FA, in which the concepts—the network domains—matter hugely to the usefulness of the method.

Iteration 4

In Iteration 4, 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 with the benefits dependency network. After the workshops, the *Alpha* and *Gam-*

ma projects had a full network containing the eight domains, as depicted in Figure 6. Through the workshops, the *Alpha* and *Gamma* project teams each found a common understanding of the projects' benefits, despite coming from different backgrounds in the organization:

> 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 teams stated that the benefits dependency network content was useful for them as part of 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 gradually discovered that for the benefits dependency network method to be sufficiently important in a workshop, it must move beyond being a static map of the dependency network assembled in a one-time workshop. It must continuously reflect what benefits the project promises to deliver, which means that the project team must revisit the network with some frequency. Although analytics projects tend to have a shorter duration than other projects in Vestas, larger analytics projects may still take years to develop. 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 appropriate for the project beneficiaries. Thus, through our evaluation, we found that the method must be incorporated into existing project governance practices in an organization. The benefits dependency network must be integrated with other development activities. It reflects commitments among the team members and what benefits they expected to deliver at a given time of the project at a given cost. Thus, the benefits dependency network assembles a kind 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.

4.3 Closing

The resulting method includes eight instead of five domains compared to the starting point stemming from IS/IT projects, cf., Figures 1 and 6. Through the iterations in Vestas, we saw how the eight domains contributed positively to creating a coherent dependency network for the analytics projects. Furthermore, the content of the network proved useful for the project team's documentation for project stage-gate approvals.

The action research study ended when Vestas officially adopted the emerging benefits dependency network method. 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 stage-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 develop the benefits dependency network tailored to analytics projects with relevant stakeholders from various parts of the organization before the project can pass a stage-gate. The following is a strong statement for Vestas concerning how, from each project in which they applied the new method, they gained more experience and knowledge on developing the network:

> 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 organization and benefits. (Senior Vice President)

Vestas decided to adopt the resulting method. As described in the study's initiation phase, Vestas and we as action researchers wanted to develop a method fit for analytics projects and accessible for practitioners. The director of data science specialists in Vestas confirmed and emphasized 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 of Data Science Specialists)

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

5 Discussion

In the following, we discuss the lessons from the action research study into the research question: *How can we improve the realization of benefits in big data analytics projects?* Extant research on benefits of big data analytics addresses the firm-level with many using a case study methodology (Conboy et al., 2020; Danielsen et al., 202; Mikalef et al., 2020a; 2020b; Wamba et al., 2017)and how, big data can help attain a competitive advantage. To address this question, this study draws on the resource-based view, dynamic capabilities view, and on recent literature on big data analytics, and examines the indirect relationship between a firm's big data analytics capability (BDAC. However, few studies are concerned with both the problem identification and improvement in practice let alone through action research.

Together with Vestas, we developed a method and elicited lessons to improve benefits realization in big data analytics projects with a starting point in previous research—more precisely (Doherty et al., 2012; Radford et al., 2014; Ward & Daniel, 2012). At the outset of the study, Vestas was dissatisfied with their benefits realization from big data analytics projects. Their data analytics projects did not systematically consider benefits realization; in particular, benefits realization was not considered after closing a project. The big data analytics projects' approaches did not match their need to incorporate a benefit focus and connect from addressing technologies to addressing benefits. Alleviating the problematic situation was not simply a question of using existing big data analytics project methodologies as they have been outlined in Section 2. A new perspective on benefits realization (e.g., Doherty et al., 2012; Radford et al., 2014; Ward & Daniel, 2012) was needed. To ensure that the benefits realization method would be useful for practitioners in a big data analytics setting, we refined its initial approach through iterative usage and adaptation in Vestas' big data analytics projects. As a result, we ended up with a useful method that Vestas could also integrate into existing their project development practices that now includes eight domains (c.f., Figure 6). Through our engagement in change, we collected data from our intervention and assessment to elicit lessons for big data analytics professional practitioners and to make distinct contributions to research. Table 2 explicates our contribution; and in the following three section we explain the contributions.

5.1 A useful benefits dependency network method for analytics

We reformulated the benefits dependency network approach that was originally developed by Ward et al. (2012) for an IS setting to become useful for big data analytics projects. From Iteration 1, cf., Section 4.2.1, we found that the domains of the original dependency network did not support the big data analytics projects' particulars. However, we confirm and support the conclusion made by Ward & Daniel (2012) that the benefits dependency network serves as a powerful framework in bridging the technology domain to the benefits domain. To make the networks useful for Vestas' analytics projects, we needed additional domains: *Outside enablers*, *Data provider*, *Data analytics*, and *Big data analytics strategy.* We thus contribute to research on value creation from big data analytics projects with the extended benefits dependency network.

In addition, the emerging method and the underlying framework depicted in Figure 6, combines the inductive and deductive approach by linking the *Data provider*, *Data analytics*, and *Benefits* domain thus establishing benefits focus to the domain *Data analytics* in which a big data analytics project may approach the big data inductively, deductively or as a combination of both. In establishing an extended framework on benefits, we concur with the claim by Lycett (2013) that we must combine an inductive and deductive approach in analytics projects. As discussed in Tamm et al., (2013) and Gao et al., (2015) if an organization solely uses an inductive approach, it neglects the focus on benefits and the value concern for big data analytics projects.

Value creation from big data analytics becomes evident when the data is appropriately managed, processed, and analyzed to generate new innovative knowledge and actionable insights (Jukić et al., 2015; Sivarajah et al., 2017). However, enabling efficient decision-making from big data analytics is not as straightforward a process as such. Aligning the right people, technologies, and organizational resources to create benefits is problematic. From their literature review, Sivarajah et al. (2017) categorize this challenge as a process challenge, which entails a group of challenges that big data analytics projects encounter, from the initial steps of capturing data to creating actionable insights. They called for empirical investigations of each of the challenges identified in their study. We present here an empirical investigation through the method that we developed over several iterations with different big data analytics projects. The benefits dependency network for big data analytics projects establishes links between benefits, organizational change activities and the needed technologies. Our method then presents a deeper understanding of the relations between each of the domains in the framework presented and how the relations are established. As a practical contribution, we present an operational way to create coherency between the domains in a workshop with representatives from each of the domains. The practical contribution also extends the research presented by Lumor et al. (2021). They present different heuristics divided between different layers of big data analytics (e.g., data processing and analysis, storage, etc.), and they call for research endeavors that can bridge the interests of actors who focus on the technical to those that focus on the social aspects of big data analytics in order to create benefits. We propose an empirically based solution to the call by Lumor et al. (2021), and we suggest aligning the right people, technologies, and organizational resources by means of the extended benefits dependency network developed specifically for big data analytics projects. We contribute based on an empirical development that bridges the field of benefits management to the field of big data analytics.

Sheng et al. (2017) also called for more research on organizational alignment for big data analytics to create actionable insights. This was later supplemented by Sfaxi and Ben Aissa (2020) and Mikalef & Gupta (2021), all outlining how big data analytics specifically demands cross-departmental collaboration in creating benefits. The emerging method fosters such cross-departmental collaboration, as each domain represents different stakeholders and departments within an organization. This finding was supported by the senior vice president in our closing evaluation of the action research. The merging benefits network method had a much greater end-to-end value chain perspective, as it bridges the big data analytics technology to the specific benefits, cf., Section 4.3.

5.2 Embedding the method into existing analytics project approaches

Embedding the network method into existing project development practices is essential for a benefits dependency network to be useful. Each of the three types of approaches, cf., Section 2.1, (1) agile principles, (2) business intelligence methods, and (3) data mining development principles have their pros and cons, which may lead an organization to prefer one approach over another (Sfaxi & Ben Aissa, 2020). For Vestas, easy embedding into existing project development practices was crucial for the success of the benefits dependency network method. An organization like Vestas does not solely work with data analytics projects; it also produces wind turbines, develops traditional IT/IS products, and has other 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 approach can have tasks developed in a project following agile principles. Our research on the network method plugs into these existing practices, as several of our studied projects used different development approaches in their big data analytics projects.

In addition, we address the concerns from Sfaxi & Ben Aissa (2020) that agile principles for big data analytics projects consider a limited set of users. Our method focus on benefits by involving various users of big data analytics technology. A benefit can be relevant for different users spread throughout the organization, and thus, the benefits dependency network manages to collect this information for the analytics project. Compared to more classical design approaches, such as CRISP-DM, our research contributes by incorporating a focus on organizational change and benefits that has previously been neglected (Shearer, 2000). As example, the DECIDE approach does not explicitly integrate a focus on organizational change and benefits (Sfaxi & Ben Aissa, 2020). In their approach, they define the preparation phase as helping to prepare the building blocks of the big data analytics projects that also must consider the business impact and putting the deployment of the big data into place. Instead, our method contributes explicitly in making the organizational anchoring and change focus concrete among the different actors in the big data analytics projects necessary for benefits realization. Thus, our method could potentially serve as a valuable integration to the already developed approach DECIDE (Sfaxi & Ben Aissa, 2020).

Further, to improve the focus on benefits realization in big data analytics, a continuous rework of the initial benefits dependency network is important. Our last iteration, cf., Section 4.2.4, found that the network is dynamic and the method must move beyond being a static method assembled in a one-off workshop. The type of benefits and requirements for a big data analytics project matures as the project matures as well going through the different stages and gates. According to and extending Davenport & Harris (2017), the benefits dependency network must ensure that the analytics project outcome is suitable for the project beneficiaries. This view is supported by Viaene & Van Den Bunder (2011), stating that the success of an analytics project is the result of the users' acceptance of the analytics delivered from the project. They highlight continuous exposure to user feedback and a willingness to alter the original project plan accordingly if these needs change. We build upon and extend their notion that continuous rework is necessary to align with changing requirements and present a continuous structured way to portray these changes. To this, we add that it is particularly useful to align a dependency network whenever a stage gate is passed in a big data analytics project.

5.3 Facilitation to create coherency

Facilitation of the benefits dependency network method is essential for big data analytics projects. From our interventions in Vestas, cf., Section 4.2, it became clear how the facilitator had a key role in steering the participants through the network domains. The facilitator brings about knowledge and competence at a general level and the participants have specific knowledge. The facilitator must ensure that the content in each domain is clustered adequately without losing detailed granularity while at the same time focusing on the less tangible benefits.

We contribute to the research on benefits management (Peppard et al., 2007; Ward & Daniel, 2012) by highlighting the importance of facilitation in building a coherent dependency network, and facilitation is even more important now that we have extended the network domains. Previous research on benefits management has not explicated in much detail how the benefits dependency workshop is facilitated. It has previously been neglected in big data analytics projects (Gao et al., 2015; Tamm et al., 2013). Big data analytics projects require a change in people's mindset (Ransbotham et al., 2016) to consume analytical insights and harvest benefits. Moreover, to avoid bias toward one of the network domains, the facilitator cannot be a key stakeholder to a specific domain in the dependency network, see Figure 6. Instead, we have found that the facilitator can be a member of the project steering committee or project owner not involved with the project's daily work.

Table 2 presents an overview of the three contributions from our action research.

Lesson	*Method support*	*Research contribution: Big data analytics benefits*	*Research contribution: Benefits realization management*
The benefits dependency network method is useful for connecting the domains supporting benefits realization in big data analytics projects.	The distinction between strategy, data analytics, data provider, and outside enablers for big data analytics projects is supported. These domains augment investment objectives, benefits, sustaining changes, and business changes, cf., Figure 6.	The benefits dependency networks respond to the challenges of realizing value in big data analytics (Lumor et al., 2021; Sivarajah et al., 2017). The lessons corroborate that cross-departmental collaboration is necessary for big data analytics benefits realization (Mikalef & Gupta, 2021; Sfaxi & Ben Aissa, 2020).	The method adds a new domain to the existing method for IS projects (Ward & Daniel, 2012) that accommodate the big data analytics strategy. The technology domain in (Ward & Daniel 2012) is decomposed to attend to big data analytics particulars.

Lesson	*Method support*	*Research contribution: Big data analytics benefits*	*Research contribution: Benefits realization management*
Embedding the benefits dependency network method into the big data analytics project practices is useful.	The benefits dependency network workshops should be held when crossing major milestones in big data analytics projects.	The benefits dependency network method is easily embedded and independent of existing project approaches, thus adding to the repertoire of methods (Kühn et al., 2018; Sfaxi & Ben Aissa, 2020; Shearer, 2000). Repeated assessment of dependency networks concurs with (Davenport & Harris, 2017; Viaene & Van Den Bunder, 2011), that continuous reassessment of stakeholder needs is necessary for big data analytics projects.	The lesson corroborates that successful benefits management for big data analytics projects as for IS projects needs to be aligned with existing management activities in the organization (Ward & Daniel, 2012).
Using the benefits dependency network method to connect the domains supporting benefits realization in big data analytics projects requires strong facilitation.	A facilitator with knowledge and competence in the benefits dependency method is central to maintaining a benefits focus for big data analytics projects.	Facilitation adds to (Tamm et al., 2013) and (Gao et al., 2015) on how to emphasize less tangible benefits. A competent facilitator can help create coherence in a benefits dependency network that extends (Ransbotham et al., 2016) on changing mindsets.	We extend the importance of the facilitator capability developed by Ward & Daniel (2012) and Peppard et al. (2007) to big data analytics projects.

Table 2. Key contributions of the study

5.4 Limitations

Our lessons and method may be transferred to similar situations for other organizations investing in big data analytics projects. As our research was conducted within a large organization involving multiple stakeholders in each project, our lessons may be transferred to situations with similar characteristics.

We acknowledge several limitations of our action research study. First, we based our results on collaboration with a single organization. Despite being involved with several big data analytics projects, extending our lessons to other organizations facing similar challenges in realizing the benefits of big data analytics projects would be needed. Extending the lessons to other organizations facing similar challenges would also add to the generalizability of these. Second, our study conceptualizes input from big data analytics projects that were still unfolding at the time of our study. Even though we report significant contributions from our lessons, there is still limited information on how the benefits of big data analytics projects become evident. We offer several means of methodological support, yet future research ought to investigate benefits realization from big data analytics after project closure.

6 Conclusion

In this action research study with Vestas, a wind turbine manufacturer relying heavily on big data analytics, we investigated how to improve benefits realization 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 that includes lessons tailored to analytics projects with big data. Our method can be embedded to existing organizational development practices and bridges the orchestration from benefits to technology in these projects. Our lessons from Vestas suggest improving the realization of benefits from big data analytics projects by:

1. Applying a benefits dependency network tailored to big data analytics projects.
2. Incorporating the benefits method into existing project development practices and their continuous rework to maintain a benefits focus.
3. Developing a workshop facilitation capability for benefits dependency networks.

Our study points to new directions for benefits realization research in big data analytics projects and how they create business value. Realizing the benefits of big data analytics projects does not solely come from implementing big data technology. Thus, future research should address how to place adequate accountability within an organization to realize big data benefits and verify organizational change activities.

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