BIG DATA IS POWER: BUSINESS VALUE FROM A PROCESS ORIENTED ANALYTICS CAPABILITY

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Abstract. Big data analytics (BDA) has the potential to provide firms with competitive benefits. Despite its massive potential, the conditions and required complementary resources and capabilities through which firms can gain business value, are by no means clear. Firms cannot ignore the influx of data, mostly unstructured, and will need to invest in BDA increasingly. By doing so, they will have to, e.g., necessitate new specialist competencies, privacy, and regulatory issues as well as other structural and cost considerations. Past research contributions argued for the development of idiosyncratic and difficult to imitate firm capabilities. This study builds upon resources synchronization theories and examines the process to obtain business value from BDA. In this study, we use data from 27 cases studies from different types of industries. Through the coding analyses of interview transcripts, we identify the contingent resources that drive, moderate and condition the value of a BDA capability throughout different phases of adoption. Our results contribute to a better understanding of the importance of BDA resources and the process and working mechanisms through which to leverage them toward business value. We conclude that our synthesized configurational model for BDA capabilities is a useful basis for future research.

Keywords: Big Data, Big Data Analytics Capabilities, Qualitative Coding, Resource-based View (RBV), process stages.

1 Introduction

The current political, economic, social, technological and environmental climate in which firms currently operate, is becoming more and more dynamic and complex. As today's firms are feeling pressure to improve their decision-making capabilities, big data provides a path to higher value and can potentially provide them with a competitive edge [1]. Therefore, currently, firms are exploring the role and use of big data as a means to address the ever-increasing complexities and as a strategic information technology (IT) investment. Since there are many definitions of terms like 'business intelligence,' 'data analytics,' 'business analytics' and 'analytics'—a term that has emerged as a catch-all term—we define big data as the massive amounts of various observational data which support different types of decisions [2]. In practice, big data enables business and IT managers and executives with a strategic tool, if leveraged effectively, can provide real-time information that can guide future moves. Although big data provides firms with many valuable opportunities, there are, however, many challenges that need to be addressed and overcome. Think, for instance, about identifying the best possible hardware and software and determining the best suitable infrastructure solution. Also, think about the cost of maintaining relevant data quality dimensions (e.g., completeness, the validity of data, consistency, accuracy), and also privacy issues related to the direct and indirect use of big data sources. In light of the above, big data analytics capabilities (BDACs) have become increasingly important in both the academic and the business environment. For now, we regard these particular capabilities as an overall competence that has multiple complementary dimensions that collectively enable firms to be competitive. BDACs are widely considered to enable enterprises to transform their current business models and value-added processes [3, 4]. If we have to believe the white papers, industry reports, and consulting studies, e.g., from Gartner, Forrester, McKinsey, Deloitte, big data analytics (BDA) will be among the most actively investigated and piloted technologies by enterprises over the next couple of years. However, talent shortages, privacy, cost concerns, and nascent offerings may impede effective firm adoption.

Despite valuable contributions in this particular domain, there is still limited understanding on how firms need to change to embrace, adopt and deploy these data-driven innovations, and the business shifts they entail [5]. Over the last years, the scope and approach of most scholarly efforts concerning BDA primarily focus on infrastructure, intelligence, and analytics tools. In turn, these contributions substantially disregard other related resources, as well as how these socio-technological developments should be incorporated into strategy and operations thinking. Dealing with these particular and aligning all organizational and IT capabilities is thus considered to be one of the grand challenges ahead to get sustainable results from technological innovations, including BDA [6, 7]. However, synthesizing from extant literature, we contend that the previously mentioned predicaments remain largely unexplored [5], severely hampering the business and strategic potential of big data. This apparent lack of foundational empirical work significantly hinders research concerning the value of BDA. Furthermore, it leaves practitioners in unchartered territories when faced with implementing such initiatives in their firms while addressing the challenges and opportunities associated with BDA.

In summary, big data is not a magical panacea; it is still data that daily processes and enterprise-wide capabilities need to incorporate. Against this background, this current paper tries to explore the process through which BDA value is obtained and explores the resources that are important when investigating BDA and how they relate to successful adoption. Achieving business value from BDA is crucial because ultimately, this value is what gives firms a competitive advantage [8]. IS research may address this particular challenge by exploring the process to generate value from BDA and which contingent resources play a crucial role in this complex, multifaceted process. While limiting our current scope, we follow the core notion of BDA value by Grover et al. [8] and regard BDA value as 'the novel and valuable insights to exploit new business opportunities or defend competition threats.'

Thus, our research questions are '*Through which process stages do firms have to go for big data analytics initiatives to add business value?*' Moreover, '*What configurations of big data analytics capability resources—for each of the distinct, but related process stages—should firms then pay attention to during the implementation of big data analytics initiatives?*'

We structure the rest of the paper as follows. The next section concerns the theoretical background of this study. Then, we proceed to outline the research methodology, present the data collection methods and our sample, as well as how we uncover patterns, relationships through the use of qualitative coding. We end this paper with main findings, followed by a discussion and suggestions for future research.

2 Theoretical background

The vast majority of current scholarship in the area of IT-business value research have grounded their arguments on the RBV of the firm [9]. The RBV is a widely acknowledged theory that explains how firms achieve and sustain a competitive advantage as a result of the resources they own or have under their control. The RBV is grounded in foundational economic scholarship concerned with firm heterogeneity and imperfect competition [10]. A 'resource' in modern research was subsequently split to encompass the processes of resource-picking and capability-building, two distinct facets central to the RBV [11]. Scholars also defined resources as tradable and non-specific firm assets, and capabilities as non-tradable firm-specific abilities to integrate, deploy, and utilize other resources within the firm Amit and Schoemaker [12]. In general, information systems (IS) studies that embrace this particular theoretical view, postulate that IT resources that are valuable, rare, inimitable and non-substitutable (VRIN) will be more likely to outperform competitors. The scholarship recognizes that competence in leveraging IT-based resources in combination with other organizational resources is a source of competitive and advantage across various industries [13-15]. These studies also suggested that firms that fail to invest in particular types of resources under specific conditions may cause the collapse of the value of the rest. Although the RBV perspective may provide some critical insights on the necessary types of IT resources that a firm must own or have under its control, it does not define how they collectively should be leveraged to derive value from them. As can be gleaned from the above, there is a need to reframe the theoretical standpoint from which IT-business value and also the value of BDA can be examined. We now focus on what BDA is.

2.1 Big Data Analytics

IDC [16] expects that from 2005 to 2020 the digital universe will grow by a factor of 300, from 130 exabytes to 40,000 exabytes. This data growth, coupled with technology advances such as open source technologies, mobile and app innovations, cloud computing, will fuel enterprises' demand for integrated BDA solutions. In the context of big data, it is important to identify the different types of resources, since the level of their infusion in various business functions can be a source of competitive differentiation [17]. When these resources and their related activity systems have complementarities, they are more prone to lead to competitive advantage [18]. To date there have been studies that attempt to define the buildings blocks of firms' big data analytics capability, that is the resources that are necessary to build upon [4, 5, 19, 20]. In essence, these scholarly contributions adopt their conceptualizations from previous IT (capability) literature, with little regard towards the particularities and conditions of the big data context. Scholars argue that it is essential to comprehend the full spectrum of factors that are relevant to obtain business value form BDA [5]. Most research is somewhat fragmented which makes it difficult to evaluate the business value.

3 Research methods

3.1 Critical literature review

The purpose of this research is to explore the process through which firms create business value from BDA and which contingent resources play a crucial role in this complicated, multifaceted process. To achieve this, we contend that it is necessary to explore the underlying phenomena and processes of BDA and explore the core body of literature to develop a clear overview and taxonomy of the phenomena of interest. Henceforth, we started a critical literature review with the primary focus on the building blocks of a BDA capability and on the possible catalysts and hindrances in attaining business value. We employed a relatively comprehensive review of BDA with the primary aim to identify the central concepts that underlie the dimensions of the theories used within the context of big data. As a final step, we tried to understand the importance of these concepts through firms that have initiated big data projects and initiatives. Table 1 shows the result of our literature review and hence the identified BDA resources and capabilities.

3.2 Case studies and data collection procedure

As our primary aim is to explore how BDA value is obtained and identify those BDA resources that are important throughout different phases of adoption, we followed a multiple-case study approach. This approach is suitable for our research, mainly because we want in-depth information about BDA phenome in practice; it allows us to present rich evidence and a clear statement of theoretical arguments [21]. This methodology is well-suited to study organizational issues [22] and allows us to gain a better understanding of how BDA resources and capabilities add value. Moreover, this approach allows us to apply a replication logic through which we treat all cases as a series of experiments that confirm or negate emerging conceptual insights [23]. We collected data through a series of in-depth, semi-structured interviews—to avoid biased responses—with field expert and senior managers from different (international) organizations, i.e., public, private, industry and consulting. Interviews are a highly efficient way to gather rich and empirical data.

Table 1. Thematic support for critical Big data analytics resources and capabilities

Big data analytics resources and capabilities	References
Tangible	
- *Technology:* New technologies are essential to handle the large volume, diversity, and speed of data accumulated by firms. Further, firms employ novel approaches for extraction, transformation, and analysis of data.	[19], [20]
- *Data:* Firms tend to capture data from multiple sources, independently of structures and on a continuous basis. Aspects concerning data such as quality, sources, methods for curating are important in deriving business value.	[24], [25]
- *Financial:* Financial resources can be considered as direct investments in support of these technologies or working hours allocated to experimentation with utilizing the potential of big data.	[20], [4]
Human Skills	
- *Technical Skills:* Technical skills refer to the know-how that is necessary to leverage the new forms of technology and to analyze the varied types of data to extract intelligence from big data.	[19], [20]
- *Managerial Skills:* Managerial skills pertain to competencies of employees to understand and interpret results extracted from big data analytics and utilize them in meaningful ways.	[20], [26]
Intangible	
- *Organizational Learning:* Organizational learning concerns the degree to which employees are open to extending their knowledge in the face of new emerging technologies.	[27]
- *Data-driven Culture:* A data-driven culture describes the degree to which top management is committed to big data analytics, and the extent to which it makes decisions derived from intelligence.	[19], [20]

Also, the interviews allowed us to carefully identify both the technical aspects related to implementation, as well as the interaction with the business side of the company. Interviewees were carefully selected using a systematic, convenient, non-probabilistic technique to gain maximal insights from different respondents who cover each relevant BDA aspect. We identified experts that have the knowledge and experience of working in a competitive and highly dynamic market which necessitated the adoption of big data as a means to remain competitive. See table 2 for an overview of all respondents. All interviews were performed face-to-face, except two interviews that were taken using Skype, in a conversational style, opening with a discussion on the nature of the business and then proceeding on to the themes of the interview guideline. When necessary, questions were clarified to encourage more accurate responses. Overall a semi-structured study protocol was followed during the investigation and during the process of collecting data [28]. In total 27 interviews were held with key and senior informants from different firms, departments—through which we obtained additional secondary company-related documents—including big data and analytics strategists, CIOs, and senior business managers. We recorded all interviews with upfront (signed) consent and subsequently transcribed them.

Table 2. Profiles of the interviewees

Firm	Industry	Employees	BDA objective	Key respondent * (*Years in the firm*)
1	Consulting Services	15.000	Risk management	Big Data and Analytics Strategist (4)
2	Oil & Gas	16.000	Operational efficiency, Decision-making	CIO (6)
3	Media	7.700	Market intelligence	CIO (3)
4	Media	380	Market intelligence	IT Manager (5)
5	Media	170	Market intelligence	Head of Big Data (4)
6	Consulting Services	5.500	New service development	CIO (7)
7	Oil & Gas	9.600	Process optimization	Head of Big Data (9)
8	Oil & Gas	130	Exploration	IT Manager (6)
9	Basic Materials	450	Decision-making	CIO (12)
10	Telecommunications	1.650	Market and service intelligence	CDO (5)
11	Financials	470	Auditing	IT Manager (7)
12	Retail	220	Marketing, Customer intelligence	CIO (15)
13	Industrials	35	Operational efficiency	IT Manager (5)
14	Telecommunications	2.500	Operational efficiency	IT Manager (9)
15	Retail	80	Supply chain management	CIO (11)
16	Oil & Gas	3.100	Maintenance, Safety	IT Manager (4)
17	Technology	40	Quality assurance	Head of IT (3)
18	Technology	180	Customer relationship management	IT Manager (7)
19	Oil & Gas	750	Decision making	CIO (14)
20	Technology	8	Business intelligence	CIO (3)
21	Basic Materials	35	Supply chain management	CIO (6)
22	Technology	3.500	New business model development	CDO (8)
23	Technology	380	Personalized marketing	IT Manager (2)
24	Basic Materials	120	Production optimization	IT Manager (4)
25	Technology	12.000	Customer satisfaction	CIO (15)
26	Technology	9	Product function / machine learning	CIO (2)
27	Telecommunications	1.550	Fault detection, Energy preservation	CIO (9)

** Note: CIO = Chief Information Officer, CDO = Chief Digital Officer*

3.3 Coding, classifying and mapping procedure

We used qualitative coding techniques to systematically analyze, organize and visualize the data [29]. We reviewed, analyzed, organized and documented all obtained data on different occasions using open coding schemes [28]. Together with the outcomes of the critical literature study as well as all transcripts from the interviews, we clustered data into a tabular structure. This approach allowed us to identify those resources and capabilities, across three phases of development, which applied to each respective case in our research. We used the applied technique iteratively to gain as much insight as possible. Two of the co-authors completed the independent coding of the transcripts by the defined themes. Each coder read the transcripts independently to find specific factors related to the required resources of a BDAC, as well as on business value derived from such investments. We repeated this process until the inter-rater reliability of the two coders (matched in pairs) was greater than 90 percent [30].

4 Findings

4.1 Phases in the development of Big Data Analytics Capabilities

Organizations need to focus on the full range of (IT) resources which are needed to build a difficult to replicate BDAC and understand through what mechanisms and under what conditions it can deliver business value [20]. We, therefore, tried to synthesize and integrate the above theoretical perspectives and working mechanisms, and combined with extant literature and outcomes from the interviews on BDA and explore their importance in driving business value. The outcome is the Configurational Big Data Analytics Capability Model (CBDACM), see table 3. The CBDACM consists of two complementary aspects, i.e., (1) the three different phases and (2) different configurations of BDA resources and capabilities tailored per phase and type of organization (i.e., SMEs and large firms). The phases—a firm has to go through in obtaining value from BDA—consist of (I) Strategic initiation, (II) Use-cases and data-driven pilots, and finally (III) Adoption and maintenance. Our model accentuates the process-oriented view on how firms can use, align and efficaciously adopt BDA to create business value. As this model is grounded in complementary resources, capabilities, and working mechanisms, it is consistent with the RBV of the firm [9], and recent literature on BDA [3, 4, 20, 31, 32]. We address each of these distinct phases in the next sections.

Phase I: Strategic initiation. The first phase according to the interviewees is about the initiation of BDA within the firms. Firms usually have to identify strategic priorities and ask 'crunchy questions.' This first step in the initiating phase is independent of the underlying data (4Vs) and therefore applicable to both traditional and BDA. Therefore, this phase requires senior management involvement and a project champion that support this significant development. Example crunchy questions might be "what are customers currently saying about our organization?", or "how loyal are our customers," "which indicators measure and represent our enterprise-wide performance?" Part of this first phase (and this might even be considered a sub-phase) is also the assessment of the current BDA capabilities. This particular assessment, by the judgment of the experts, is crucial for the identification of both the scope and requirements for BDA initiatives as well as the capabilities. The standard assessment could include (but is not limited to) data and systems, general BI and analytics maturity and capabilities and related skills sets1, potentially other relevant aspects like formulated IT strategies, priorities, policies, associated budgets, and investments. These capability assessments are crucial for identification of the scope and requirements of data-driven and big data initiatives.

"…Data, infrastructure, system and application assessments allow us to provide valuable information about the data assets that can be leveraged."

Phase II: Use-cases and data-driven pilots. Based on our analyses, we identified a second phase, i.e., Use-cases and data-driven pilots. Interviews show that the first step in this second phase is the identification and definition of various 'Use Cases.' In this step, challenges within strategic focus areas are identified based on specific and explicit business need, ambitions, requirement and also possible suitability for BDA, i.e., 'the problem.' Various experts pointed out that these use cases (or stories for that matter) should define 'the problem' relative to the foreseen analytical data lifecycle (consisting of the following cycle steps: collecting, processing, analyzing, reporting and archiving/maintenance). After this, firms should, in essence, define a technical approach by identifying a suitable approach based on the data lifecycle, volume, variety, and velocity (or even 4V). Moreover, in this process, a clear distinction should be made between analytical techniques that scale up existing (analytic/data) assets and the once that provide the firm with new relevant data perspectives. Our coding process suggested that this part of the Use Case is followed by the refining of a particular business decision based on analytic results. Outcomes suggest that a second sub-phase of the Use-cases and data-driven pilots phase, thus, concerns the roll-out of pilots and possible prototypes. This phase is an essential part of this phase as it could save valuable time and money for firms as firm target value providing initiatives. A key attribute for data-driven pilots is the involvement of the leadership. The following excerpt from a senior manager clarifies this view:

"*Ensure direct connection to the business decisions and stakeholders involved to generate and evaluate results quickly.*"

In this process firms should also seek for low-risk, high-value pilot projects as these might be able to contribute to the foundation for BDA capabilities while simultaneously cultivating early, and sustaining sponsorship.

Phase III: Adoption and maintenance. The final phase is about the adoption and maintenance of BDA initiatives. Conceptualization of our coding procedures suggests that adoption situationally requires both organizational change and a robust technical environment should be maintained. Interviews suggest that within this phase firms need to exploit talent, user skills, innovative technologies, and best-practices to continuous iterative exploration and investigation of past business performance to gain insight and drive business strategy. This step also links this final phase to the first one. So, our outcomes suggest that for every type of big data solution firms need to embrace agility,

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[1] As no single person has all the required skills for BDA success, typical assessments should cover skill sets across teams, departments in order to identify possible skill gaps and development needs.

while at the same time (technical) data governance needs to be in place to deliver business insights cost-effectively. What we understand from all the interviewees is that BDA capability transformations require both hard and soft skills and firm resources. Moreover, as most firms have been heavily investing in enterprise systems to streamline their processes and recently started cultivating a mindset that focusses on analyzing data and information to improve performance.

"We see a clear shift from what modern firms and business and IT executives need to do, an innovative process of automating, to what they need to know on a daily basis."

4.2 Configurations among the Big data analytics capabilities

Through our analyses, we identified a coherent set of concepts and notions. Collectively, these resources, i.e., 'Tangible,' 'Human Skills,' and 'Intangible,' comprise what is referred to in the literature as a big data analytics capability. In this research, we apply a practical mapping approach following a configurational approach [33] using our rich qualitative data from the interviews. Configuration theory views a multitude of variables simultaneously through a 'holistic' lens. Thus, different configurations of these (BDA) capabilities can yield superior performance (or 'business value'). Hence, we visualize each possible combination of resources and capabilities of these solutions (of grouped firms) in the form of a matrix. In our research, we use black circles (●) to denote that the particular resource was important. Blank circles (○), on the other hand, indicate the absence of it in the investigated cases. In doing so, we try to elucidate patterns of elements that collectively lead to our focal outcome of interest.

Table 3. Configurational Big Data Analytics Capability Model (CBDACM)

	Phase I			**Phase II**		**Phase III**		
	I	II	III	IV	V	VI	VII	VIII
Context								
Large	●	●		●		●	●	
SME			●		●			●
Resources								
Tangible								
Technology		○		●	●		●	
Data		○		●		●	●	●
Financial	●	●	●		●	●		
Human Skills								
Technical Skills	○			●	●	●	●	
Managerial Skills	●	●					●	●
Intangible								
Organizational Learning				●	●	●		●
Data-driven Culture	●	●		●			●	●

We currently do not distinguish between the main elements of a particular configuration with larger circles and minor elements (less critical) with smaller ones. Blank spaces can be considered an indication that the specific condition is insignificant or a don't care situation in which the condition may be either present or absent. Also, for each phase, we distinguish patterns of elements for two types of firms, i.e., A) SMEs and B) large firms. Table 3 shows the importance of each resource across the three phases.

Solutions I and II correspond to large firms. In both solutions, financial and managerial skills are essential for the initiation of BDA within the firms. Solution III, however, applies to SMEs where analyses showed explicit support for financial resources as a direct investment in the support for BDA. Within Phase II we can distinguish two solutions (IV and V). Firms of solution IV (corresponding to large firms), showed a strong presence of tangible and intangible resources, and human skills. The focus for these firms in this phase is now on the know-how that is necessary to leverage BDA technology and to analyze data. On the other hand, firms of solution V, which were in the SME size-class, continued to show the presence of technological and financial resources as well as slight focus to extend employee knowledge in the face of emerging technologies. Finally, within the final phase, we identified three solutions of grouped firms. Solutions VI and VII focus on strong tangible resources, while the final solution (SME size-class) shows agility in tangible resources and human skills, while the focus is on accentuating and strengthening the already present data-driven culture and knowledge extension capability. These configurational forms in which firms create business value from BDA capabilities demonstrate an asymmetrical relation as their composition differs across three different phases differ. These fine-grained outcomes shed light on necessary capability conditions that co-exist and drive business value. Our outcomes align well with recent studies that argue that specific combinations of firm resources, competence, and capabilities enable firms to survive, thrive, and support evolutionary fitness with the external environment [34, 35].

5 Discussion, concluding remarks and future work

This study tried to unfold and get a better understanding—through 27 interviews with field experts—of the process through which BDA value is obtained and explores the importance of complementary resource and capabilities, as well as factors that enabled or hindered the potential value of big data investments, throughout the different phases. This research, therefore, makes several contributions to the current BDA research base. First, our study contributes to the emerging literature of capturing the business value of BDA investments [4, 19, 20]. Second, we examined the different configurational forms in which firms generate business value from BDA. Finally, this study synthesized the CBDACM from the literature and subsequently extended and validated this model through interviews with big data field experts and consultants. Moreover, our configurational model highlights the importance of different configurations of resources tailored per phase. These configurations—that views a multitude of variables simultaneously through a ‘holistic’ configurational lens—differ per phase, as each phase focusses on different BDA aspects to create business value. These outcomes are essential because we demonstrate and contend that several important factors need to consider when implementing big data projects and initiatives. In terms of practical implications, our study unveils to managers the potential process and core-resources they should focus on when planning to delve into a big data analytics projects. Our model suggests it is imperative to turn data into actionable intelligence by developing the BDA capability to look forward, inform and optimize decision making. What is important, is that firms keep aligning their BDA initiatives with business needs. Practitioners should, therefore, understand the firms’ ambitions, the business strategy, and key performance indicators, and then work backward to determine what information and analysis are needed to support those priorities. Big data must cut across the entire firm, and executives and decision-makers have a crucial role in creating awareness. Typically SMEs can achieve this easier than larger firms. When most important stakeholders know why big data is essential and how they are expected to contribute, firms can avoid significant missteps. Training and education, in that respect, are key tools for making sure everyone is on board. Also, BDA quite often requires widespread changes to processes, data standards, governance, organizational structures, governance, and IS/IT. Firms should therefore effectively focus attention on building broad-based support and helping the organization overcome resistance to change. As a first step, firms should be deploying an honest assessment—in understanding the current BDA capabilities—and the emerging gaps they will need to close to get more value from BDA investments.

There are limitations regarding our study. First, we currently only did interviews with the goal of obtaining a deep and rich understanding of BDA. Although our study is a decent starting point, we cannot generalize the outcomes based on the current scope of analyses. Future research could build on these outcomes and further validate the constructs through, e.g., survey research. A large-scale quantitative analysis could provide more granularity towards the conditions and limits to which big data analytics add value, and shed some light on contextual factors that are of importance, mainly using a complexity science approach [35]. Also, we currently did not explicitly compare across industries, companies of different size and countries. These are also avenues for future research. Future research could then also explore how firms can synthesize and define improvement activities that best meet firms' current and future innovation needs. Finally, future research could investigate the conditions that coerce firms to start investing in big data, such as competitive pressures, as well as lag effects which may delay the realization of business value.

To conclude, our contribution to the big data theory and practice accentuates the process-oriented view on how firms can use, align and efficaciously adopt BDA to create a sustained business advantage. We argue that the CBDACM is a useful contribution to the literature on how firms gain value from BDA efforts.

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