Building Data Analytics Capabilities for Value Creation: A Resource-Based View

Short Paper

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Abstract

Digitalization has made large amounts of data available for business organizations and the availability of data can also enhance their business performance and transform their business. To deploy data for value creation, business organizations should have data-related resources and build capabilities using these resources. The objective of this research study is to explore the role of data-related resources such as data, data infrastructure, data-related human resources in building data analytics capabilities (DAC) for achieving business performance. The study also aims to understand the integration of data-related resources in building DAC. We think that the integration of data-related resources is necessary for the creation of data-enabled intangibles which is closely linked to the level of DAC in organizations. The study develops a conceptual model which will be evaluated and refined via interviews conducted with various business organizations in Finland. Practical suggestions will be provided to business organizations based on the findings.

Keywords: Data-enabled intangibles, data analytics capabilities, resources, resource-based view, business performance.

Introduction

Nowadays, data has been argued to be a key resource for business organizations (Li et al., 2016). Digitalization has made huge amounts of data available to business organizations whereas the availability of data can also enhance business organizations' competitive advantages and transform their business operation (Vial, 2019). For example, social media data has become an important resource for service organizations to understand their customer experience and satisfaction (Miah et al. 2017; Božič and Dimovski 2019). Manufacturers are transforming their business operations based on data-driven insights and actions (Lee et al., 2020).

Business organizations are making use of data analytics (DA) in their business to get valuable information, knowledge, and insight from data, which can lead to value creation. Data analytics capabilities (DAC) has been argued to be vital to achieving value based on DA. Prior literature has studied DAC from different angles. Park et al. (2017) examined DAC from the view of information processing and dynamic capabilities. Some scholars investigated DAC from the business model perspective (H.-M. Chen et al., 2017) and ecosystem perspective (Gust et al., 2017). Resources are necessary components that help build an organization's capabilities (Wade & Hulland, 2004), and these resources are organization-specific and are rooted in complex business processes (Bharadwaj, 2000). DAC will be dependent on various data-related tangible and intangible resources, such as data, data infrastructure, and data talent (Gupta & George, 2016). However, little research has attempted to explain DAC in organizations from the resource-based view (RBV) (Barney, 1991) though the importance of resources in building DAC has been highlighted in the literature (Mikalef et al., 2020) and RBV is a good theory to understand how resources can be applied to build capabilities for value creation (Kohli & Grover, 2008). In addition, different data-related resources are needed in building DAC and there is a lack of knowledge on the integration of different resources from the RBV perspective, particularly, how different data-related resources can be applied to generate data-enabled intangible resources like new knowledge and insight for business from the RBV perspective.

To address the above gap, this study develops a conceptual model to explain DAC based on RBV. The RBV can help identify the resources that are necessary for building DAC since organizations need access to resources with which they can create data-enabled intangibles. Generating data-enabled intangibles are socially complex processes involving technology, human, and other organizational resources. The creation of data-enabled intangibles requires the integration of data, technology, and human resources. Data-enabled intangibles are unique resources specific to data-driven processes, which brings new insight or knowledge for business (Tao et al., 2018). Thus, in this study, the concept of data-enabled intangibles such as knowledge and insight were introduced as intangible resources to explain how data, data infrastructure and data-related human resources can be applied to generate valuable intangible resources for building DAC and creating value. This study aims to 1) identify the data-related resources needed for building DAC from the RBV perspective (access to resources), and 2) investigate the integration of different data-related resources for building DAC (resource integration).

The remainder of this paper is structured as follows. In the next section, the theoretical support for the study is provided by discussing the RBV and data-related resources. Then, we discuss the conceptual theoretical model and the related propositions followed by the discussion of the planned research method in this study. Finally, the expected contributions and limitations of the study are presented.

Theoretical Background

The resource-based view

The resource-based view (RBV) of the firm introduced by Barney (1991) has been widely applied in the field of information systems (IS) to explain how organizations can apply IS to get competitive advantages (Kude et al., 2018; Luo et al., 2016). According to the RBV, organizations can achieve sustained competitive advantage in their industries by applying different resources such as physical capital, human capital, organizational capital, etc. Some scholars define resources to encompass both assets and capabilities. Capabilities can be defined as an organization's ability to deploy its resources for value creation (Amit & Schoemaker, 1993). In this regard, an organization's strategic success and competitive advantage are dependent upon its ability to deploy resources effectively (Piccoli & Ives, 2005). Based on RBV, Ayabakan et al. (2017) developed a framework to measure IT business value through the role of IT-enabled production capability. Ray et al. (2005) used RBV to study the positive effects of IT on the customer service process. They found that IT can create IT capabilities when IT is diffused at the process level since IT capabilities are socially complex and path-dependent which can explain the performance differences among organizations.

The RBV states that resources should be heterogeneously distributed across organizations and must be immobile i.e., organizations must have unique resources that differentiate them from others. This uniqueness is what determines their ability to create value better than others and to stay ahead of the competition. Accordingly, the uniqueness of the resources is determined by the resource attributes presented by the RBV (Barney, 1991). i.e., resources must be valuable, rare, inimitable (difficult to imitate), and non-substitutable. In this regard, not all organizational resources carry all four resource attributes. Some of the resources may be valuable but not rare, some resources may be valuable and rare, but they cannot promise a sustained competitive advantage. Only inimitable resources can help an organization to achieve sustained competitive advantage as they can be valuable, rare, and not easily substituted (Iyer et al., 2006). This is because an organization's inimitable resource is contingent upon its unique historical conditions, the reason for competitive advantage may be causally ambiguous (not understood perfectly), and finally, due to social complexity, meaning that the resource is generated due to complex social phenomena involving many organizational factors that are difficult to conceive of by other organizations (Barney, 1991). Based on the above discussion, we consider DAC to be an important organizational resource that can be leveraged to create value, such as achieving competitive advantages and business performance.

Prior research in IS field show that RBV is an appropriate theoretical framework to explain the resources needed for building DAC, and for data-driven value creation (E.g., competitive advantages). To build DAC and to create value, organizations need access to data-related resources such as data, data infrastructure, and data-related human resources. However, their access to data-related resources cannot guarantee their DAC and value creation. Hence, organizations should integrate various data-related resources efficiently to create intangible resources such as new knowledge and insight for business. The new knowledge and insight from resource integration could generate new resources for organizations which are rare and have high value for organizations. Therefore, RBV is applied in this study to explain not only the needed resources for building DAC but also how these resources are integrated to generate new intangible resources (e.g., knowledge and insight) which will be critical for the determining the level of DAC and the data-driven value creation in organizations.

Tangible and intangible resources

Resources can be categorized as tangible and intangible resources. Tangible resources are resources that have a physical presence. An organization's equipment (e.g., machinery), technological infrastructure components and other organizational systems fall under the category of tangibles (Karimi et al., 2007). As mentioned earlier, resources must have attributes that enable organizations to create and sustain competitive advantages. Tangible resources are valuable. For example, having an up-to-date technological infrastructure is valuable and sometimes even rare depending on the organization's annual technology investments and the application of updated technologies. However, these resources can be easily procured by competitors in the market. Similarly, the same argument can work on other tangible resources like machinery and components. Information regarding tangible resources is available for competitors and therefore they can take actions to be at par with the competition by procuring these resources without much difficulty (Barney, 1991). Even if organizations are not able to source similar resources, they can acquire their substitutes which can provide similar functionality to the competitors' resources. Thus, tangible resources can be valuable and rare, but they can be easily obtained by business organizations' competitors.

Intangible resources can be classified into human resources and organizational complementary resources. Human resources include skills or know-how, knowledge, experience, learning, and relationships (Drnevich & Croson, 2013). Whereas, organizational complementary resources include organizational structures, planning systems, and organizational culture (Barney, 1991). Intangible resources are responsible for the successful implementation of organizational processes (Leidner et al., 2018). The skills of human resources such as technical and managerial skills are valuable and rare. As human resources tend to learn through experience, developing a skilled human resource can take some time. However, over time these human resources can be acquired by competitors. Therefore, human resources are not inimitable, and organizations can source skilled human resources from outside. On the other hand, organizational complementary resources namely brand reputation, customer satisfaction, organizational structures, planning systems, and organizational culture are a part of an organization (Hall, 1993). Different departments within an organization contain human resources, their own mechanisms to perform their duties, and in short, their behavior, methodologies, and the way they interact with each other can define their organizational culture (Vial, 2019). Therefore, these resources are non-imitable as they appear to be socially complex. Therefore, an imitating organization can simply acquire the top management team or the head of the organization to try and implement something similar, but they would not be the same. However, they might be able to create their own unique organizational culture. Therefore, organizations can try to imitate their competitor's organizational culture, but it won't be similar.

In this study, we consider data and data infrastructure as both tangible and intangible resources. Data is tangible because it is available publicly from various sources. Examples include government data, community data from social media platforms like Facebook and Twitter. The data from these sources can be used as inputs in the process of building DAC and similarly, data can be created via processes that are organization-specific and cannot be gathered from outside which is also known as internal data. The intangibility can come from its quality, reliability, and accuracy which can act as a rare, valuable, and inimitable resource for the organization. Data infrastructure includes both hardware and software. Data infrastructure include some tangible resources and can be sourced externally, such as data warehouse, cloud computing, etc. However, it can act as an intangible resource when combined with data, software, and human resources. The intangibility of data infrastructure is related to how effectively it is combined with other resources to build DAC and create value. In this regard, the software is also an intangible resource as it does not have a physical presence. On the other hand, Human resources are intangible because they contain the skills, knowledge, and experience to deploy tangible resources to build DAC and to create value.

Theoretical Model and Propositions

Proposed conceptual model

This study develops a conceptual model based on the RBV. Specifically, data-related resources such as data, data infrastructure, data-related human resources, and data-enabled intangibles are needed for building DAC, and DAC could lead to value creation, e.g., business performance. The definitions of these concepts are presented in Table 1.

Constructs	Definition
Data	Data as a resource is a collection of facts and figures relating to a business (Grover et al., 2018).
Data infrastructure	Data infrastructure can be defined as a technological resource consisting of hardware and software components that are necessary for collecting, storing, processing, analyzing, visualizing, and sharing data and information across the organization (Bharadwaj, 2000).
Data-related human resources	Data-related human resources are an organization's human capital comprising of employees who are skilled in technical and managerial aspects of DA (Bharadwaj, 2000).
Data-enabled intangibles	Data-enabled intangibles consist of one or more intangible resources that are enabled in the processes of combining data, data infrastructure, and data-related human resources (Bharadwaj, 2000). This study focuses on the new knowledge and insight generated in the processes of combining data, data infrastructure, and data-related human resources.
DAC	The ability of an organization to deploy data, technology, and human resources to create data-enabled intangibles determines its DAC (Shuradze & Wagner, 2016).
Business performance	Business performance refers to an organization's ability to achieve significant cost savings, revenue growth, enhanced return on investment, customer retention, profitability, etc. (Chae et al., 2014; Y. Chen et al., 2014; Tippins & Sohi, 2003).

Table 1. The definitions of the concepts included in the conceptual model

Availability of data and having a variety of data sources can help companies to perform DA based on various business needs. An organization's data sources may include internal, external, and open data sources. Data infrastructure consists of hardware and software components. For example, infrastructure components include data collection technologies, servers, computational technologies, data warehouses, analytics, and visualization tools. While data-related human resources consist of technical skills and managerial skills. Examples include data analysts, data scientists, business managers, data strategy leaders, etc. Data, data infrastructure, and data-related human resources must be combined to produce data-enabled intangibles, thus building DAC. The data-enabled intangibles consist of knowledge, capabilities, organizational culture, and synergistic outcomes all of which are enabled by the combination of data, data infrastructure, and data-related human resources. The data-enabled intangibles further determine the level of DAC in the organization, which is an important organizational resource that generates business performance. In the model, business performance is the outcome that the organization can create. For instance, an organization would like to achieve business performance in terms of cost-effective operations or by achieving substantial revenue growth. The proposed conceptual model is shown in Figure 1.

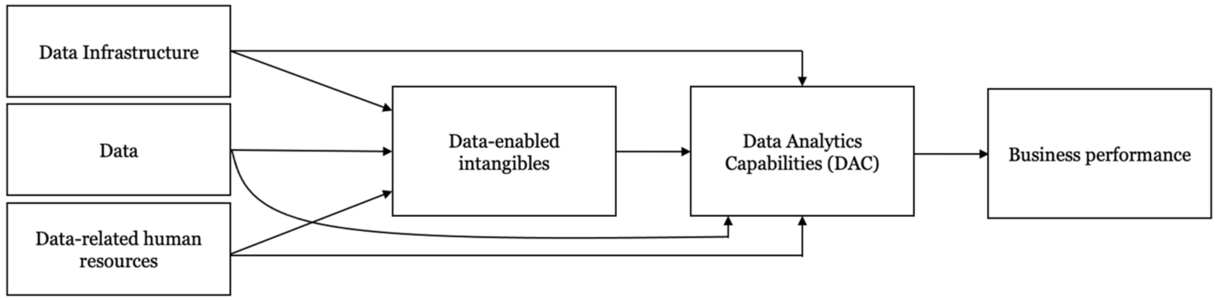

Figure 1. Conceptual model

Proposed Propositions

Data is a primary ingredient in the process of building DAC and is available in new forms and can be collected from various sources (Gupta & George, 2016). Due to the increasing number of data generated by people, sensors, and devices, organizations are now having to deal with data that is high in volume, velocity (high speed), variety, and veracity (accuracy) (Grover et al., 2018). For organizations to perform DA, the context and the data related to the context matter. Therefore, organizations must be able to source data that is reliable and accurate for performing DA. For instance, in air pollution management, the presence of pollutant data, meteorological data, and sensor data is needed for achieving predictive capability (Zhang et al., 2019). However, data is only one of the many components in the DAC-building process. Building DAC requires the involvement of both technology (data infrastructure) and human (data-related human resources) components. Hence, we propose that:

Proposition 1: Data is necessary but not sufficient to create DAC.

Data infrastructure is an important resource in building DAC. Data infrastructure consists of hardware and software components that are necessary for data collection, storage, gathering, analysis, visualization, and data-enabled knowledge sharing across an organization (Krishnamoorthi & Mathew, 2018). Therefore, data infrastructure must be integrated into the organization to leverage the complete value of data. As mentioned earlier, data infrastructure components can be acquired with ease. Organizations can leverage data infrastructure to build data related applications that revolve around their business operations (Fink et al., 2017). However, integrating the data infrastructure into organizational business processes requires investment, expertise, and time, which help generate a unique organizational resource for DAC. Appropriate use of data infrastructure can lead to improvement in their offerings. In addition, the software tools are important for performing various DA tasks namely descriptive, predictive, and prescriptive analytics (Grover et al., 2018). They also help in visualizing important information in real-time which can be helpful for taking actions based on the insights offered by these tools (H. Park et al., 2016). Data infrastructure cannot create DAC by itself as data is a vital ingredient that is stored and processed in data infrastructure. In addition, data-related human resources are the ones orchestrating the process of DA using data and data infrastructure. In this regard, we propose that:

Proposition 2: Data infrastructure is necessary but not sufficient to create DAC.

Data-related human resources are the human components of the organization that is responsible for handling data (Gupta & George, 2016). The technical skills for handling data are vital for DA. These skills are essential for understanding the data, knowing how to use different software tools appropriately for different types of analysis, and converting the data into useful information (Shuradze & Wagner, 2016). Human resources with technical skills provide the lens for the organization to witness valuable information from organizational data sources. On the other hand, managerial skills are essential for efficiently managing the functionality with regard to DA applications (Bharadwaj, 2000). Managers must know why they are using DA. They shoulder the responsibility to create the mechanisms required for assimilating DA knowledge into organizational functions (Teo et al., 2016). These skills are not easily imitated due to the factors such as organizational learning and experience gained from the successful implementation of DA projects. The learning can take a long time and generates tacit knowledge into both sets of human resources and may create a link that is hard to imitate perfectly (Piccoli & Ives, 2005). In this regard, the coordination between the managerial and technical human resources is related to the success of DAC. However, the human resources need other data-related resources such as data and data infrastructure to store, analyze, and visualize data which is an important antecedent for human sense-making. Therefore, we propose that:

Proposition 3: Data-related human resources are necessary but not sufficient to create DAC.

The presence of data-related human resources and data infrastructure provides the support required for creating new organizational intangibles. As human resources work with data infrastructure, they must succeed in integrating data infrastructure into organizational operations. In other words, they must embed data infrastructure into organizational processes which can generate new knowledge depending on where and how it is being embedded (Rai et al., 2006). Integrated data infrastructure provides the flexibility required to introduce different applications based on the needs of the organization (Bharadwaj, 2000). Once data infrastructure is embedded into organizational processes, it can enable an organization to create a data-enabled capability which can either be a new capability or an improvement over an already existing capability in the context of data-driven operations. As organizations make use of data-related resources to create data-enabled intangibles, the shared values/beliefs, coordinating mechanisms, organizational DA practices are uncovered in the process which further defines their culture concerning the use of data and data resources. Finally, the shared practices between different members can develop synergies across the organization. For instance, synergies can lead to the efficient and quick development of new products and services to be offered to the customers which may otherwise take a long time (J. L. Chen, 2012).

Though data-enabled intangibles consist of human insight and knowledge, organizational data culture, synergistic business processes & systems, organizational reputation, relationships, etc. (Barney, 1991; Bharadwaj, 2000; Drnevich & Croson, 2013). This study focuses on the knowledge and insight from the human resource perspective. Data and data infrastructure should be applied in business by human with skills and knowledge to solve business problems or perform business tasks in organizations (Schymanietz & Jonas, 2020). When organizations integrate data-related resources, e.g., a data analyst/scientist using data infrastructure to gather data to make analysis, new knowledge or insights are generated for business, which otherwise cannot be created without the integration of these data-related resources (Kim et al., 2011; Kleis et al., 2012). The unique intangible knowledge and insight cannot be acquired in the traditional business process or from external organizations. Therefore, we posit that:

Proposition 4: Combination of data, data infrastructure and data-related human resources are necessary for the creation of data-enabled intangibles.

The creation of data-enabled intangibles can take time and effort. Moreover, they are enabled due to the integration of data-related resources and can be socially complex in an organizational setting. In this regard, data-enabled intangibles cannot be imitated easily, or they cannot be perfectly imitated. Therefore, they are valuable, rare, and not easily substituted by competitors. Data-enabled intangibles are unique organizational resources that are hard to imitate and can ensure an organization's sustained competitive advantage. The way the intangibles operate is not easily explained due to the causal ambiguity surrounding these intangibles. The process by which an organization can successfully assemble data, data infrastructure, and data-related human resources to create data-enabled intangibles determines its DAC. Thus, we propose that:

Proposition 5: Data, data infrastructure, data-related human resources, and data-enabled intangibles determine the level of DAC in an organization.

DAC is highly embedded in the processes related to the deployment of resources and are specific to an organization, can be invisible, and therefore has the potential to generate business performance. DAC has been argued to improve an organization's business performance. For example, Müller et al. (2018) found a four percent increase in organizational productivity due to DAC across all industries. By leveraging insights generated through DAC, firms could achieve competitive performance by developing other organizational capabilities, such as marketing and technological capabilities (Mikalef et al., 2020). Krishnamoorthi and Mathew (2018) found that DAC can lead to business performance by supporting decision making, improving processes, increasing profits and revenues. Therefore, we propose the following proposition.

Proposition 6: DAC is related to the business performance of an organization.

Planned Research Method

A multiple case study will be applied in this study to evaluate the conceptual model. The multiple-case study findings could strengthen the generalizability of the case studies and induce confidence in the findings as evidence is gathered from multiple sources (Yin, 2011). This type of method is suitable for finding answers to our research, as we intend to find out which resources are needed for building DAC and how the resources are linked with each other to build DAC. Therefore, we are taking an explanatory approach to finding answers. We will target small, medium, and big companies from different industries. In doing so, we can identify the variances among them. The research will be carried out in Finland. We will conduct interviews in at least three companies. The interviews will be semi-structured, and we will conduct interviews with at least five employees in each company who are involved in data and data analysis in their business. Overall, a sum of 15 interviews will be carried out in this study. The interviews will be organized either through an online or face-to-face meeting. Each interview will be about 60 to 90 minutes. All interviews will be recorded with the permission of the interviewees, and the data will be kept confidential for reasons concerning privacy and information security. Qualitative analytics software like NVIVO or Atlas will be employed for analyzing the interviewed data.

We will collect data about the interviewee's position and responsibility in the case companies. The interview content will be related to the resources in building DAC, such as data, data infrastructure, data-related human resources, and data-enabled intangibles in the case company. The content will also include details regarding how the data-related resources are associated with each other to build DAC, how they determine the level of DAC, and how DAC can lead to business performance will also be asked in the interviews. The answers will help us evaluate the conceptual model and further make changes to the model.

Expected Contributions and Research Limitations

Through this study, we contribute to the literature on DAC by exploring how data, data infrastructure, and data-related human resources can be combined or integrated to generate new resources, specifically data-enabled intangibles. Therefore, the contribution is twofold. First, this study highlights the importance of access to data-related resources in building DAC. Second, the study extends the understanding of DAC building by explaining the integration of needed data-related resources in generating data-enabled intangibles, which is vital for DAC level of organizations. Based on the multiple case study this study aims to provide evidence on the role of different data-related resources in creating DAC, which will be a unique organizational resource and can help companies to generate value.

This study aims to provide a practical contribution to business organizations by providing them practical suggestions on different data-related resources for building DAC for value creation as well as how the combination of different data-related resources can help generate new intangible resources for building DAC. The research findings will provide companies with a comprehensive understanding of the importance of the combination of data-related resources in building DAC. The findings will encourage companies to invest in data-related resources for building DAC for value creation. Meanwhile, the findings in this study might also offer companies that have not succeeded in building DAC for value creation some practical guidelines on how to enhance their DAC by investing in data-related resources.

This study has its limitations. First, this study applies the RBV theory and has not considered other IS theories which might also provide an explanation with regards to value creation in organizations via building DAC, for example, from the perspective of strategic alignment, dynamic capability, resource complementarity, etc. Second, we use a multiple-case study methodology with case companies in Finland, which might limit the generalizability of the results to other contexts and countries. Therefore, future research can use other research methods, such as large-scale quantitative survey, to validate and further develop the conceptual model. Third, this study only considers the role of data-related resources in building DAC in organizations, other organizational resources, such as leadership, business capability, innovation capability, have not been considered in this study. Future research can consider investigating DAC from a much broader view of resources based on the RBV. Fourth, this study has not considered the external factors such as government regulations and industry competitiveness in explaining DAC building, which should be taken into consideration in future research.

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