From Big Data Analytics to Dynamic Capabilities: The Effect of Organizational Inertia

Completed Research Paper

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Abstract

While big data analytics have been credited with being a revolution that will transform the way firms do business, there is still limited knowledge on how they should adopt and diffuse these technologies to support their strategies. The purpose of this paper is to understand how different inertial forces related to deployments of big data analytics inhibit the formation of dynamic capabilities and subsequently performance. We draw on a multiple case study approach of 27 firms to examine the different forms of inertia that characterize big data analytics implementation. This study provides empirical evidence that contributes to the scarce research on deployment of big data analytics to enable dynamic capabilities. Disaggregating dynamic capabilities into the sensing, seizing, and transforming, we find that different forms of inertia including economic, political, socio-cognitive, negative psychology, and socio-technical affect the formation of each type of underlying capability.

Keywords: Big data analytics, organizational transformation, inertia, deployment, IT-enabled transformation

Introduction

In spite of big data analytics being in the spotlight of attention of researchers and practitioners for almost a decade now, there is still very limited research on what forces can potentially hinder the potential business value that these investments can deliver. Most empirical research to date has emphasized on the necessary investments that firms must make or the complementary resources they should take into account in order to realize business value from big data analytics (Gupta and George 2016; Mikalef et al. 2017). Nevertheless, the process from making the decision to adopt such technologies, to assimilation and routinization, leading up to turning insight into action is seldom discussed, particularly with respect to inertial forces that take place. The underlying premise of big data dictates that such investments can generate insight with the potential to transform the strategic direction of firms, and help them outperform competition (Prescott 2014). Yet, this process entails organizational transformation at multiple levels, and as with any case of organizational transformation, is subject to path dependencies, routinization, and other hindering forces (Sydow et al. 2009). Such forces of inertia can have a detrimental effect on the business value of big data analytics investments, and even be the source of project failure.

While the literature on big data has extensively documented the importance that organizational learning, a data-driven culture, and well-defined governance policies have on overall project success (Kamioka et al. 2016; Kamioka and Tapanainen 2014; Mikalef et al. 2019a; Mikalef et al. 2019b; Vidgen et al. 2017), there is to date a very limited understanding on how these should be implemented and what factors may inhibit successful deployment or even adoption. Even more important is the link of big data analytics deployments with firm strategy, and the utilization of generated insight to sustain a state of competitive advantage. Recent work has demonstrated that big data analytics can impact a firm's dynamic capabilities, which are the primary source of sustained performance gains (Wamba et al. 2017). Dynamic capabilities are associated with an enhanced ability of a firm to react adequately and timely to external changes, and require that a series of capabilities are put into action (Eisenhardt and Martin 2000). The presence of strong dynamic capabilities has been linked to increased agility, and enhanced innovativeness, key components of competitive success in contemporary markets (Mikalef and Pateli 2017). Based on the work of Teece (2007, dynamic capabilities can be decomposed into the activities of *sensing*, *seizing*, and *transforming*, which jointly contribute towards enabling firms to achieve superior and sustained performance. On bridging the gap between big data analytics and the effect on dynamic capabilities, there is still not much attention on the processes of big data adoption and implementation. To date, most studies have attempted to provide a narrative on how big data can produce value (McAfee et al. 2012), or even empirically show an association between investments and performance measures (Gupta and George 2016; Mikalef et al. 2019a; Wamba et al. 2017). Yet, in reality managers and practitioners are faced with a number of hurdles which need to be overcome, on individual, group, organizational, and industry levels. Even though there is the general assumption that these barriers are mostly prevalent during the early stages of big data adoption, prior studies on other technological innovations suggest that they emerge in different stages of diffusion and assimilation (Limayem et al. 2003).

This study builds on the previously mentioned gaps and attempts to understand how inertial forces hinder the potential value of big data analytics. Specifically, we examine the role of big data analytics in the formation of dynamic capabilities and try to isolate key barriers that are caused by inertial forces and path dependencies during big data analytics adoption, diffusion and routinization. To do this we build on past literature of organizational transformation and inertia, and identify five main sources of inertia, *negative psychology inertia*, *socio-cognitive inertia*, *socio-technical inertia*, *economic inertia*, and *political inertia*. We then procced to explain the main stages of adoption and diffusion, which include intrapreneurship and experimentation, coordinated chaos, and institutionalization. The different stages of adoption and the types of inertial forces are then mapped onto the three underlying processes of dynamic capabilities, i.e. *sensing*, *seizing*, and *transforming*. Doing so enables us to detect the different forms of inertia, and the stages at which they emerge. In addition, by understanding how the inertial forces impact the processes that underlie dynamic capabilities, it is possible to better capture effects of performance, and how they may be hindered at different levels. The outcomes of this study provide important implications for practice also as they enable managers to understand how big data analytics deployments relate to their firms strategy and operations, and at which levels inhibiting forces may act. Hence, this research is driven by the following research questions which helps guide our investigation:

> *RQ1. What forms of inertia are present during big data analytics implementation projects? How do these manifest during the different stages of adoption and diffusion?*
>
> *RQ2. How do inertial forces during big data analytics implementation projects affect a firm's dynamic capabilities?*

To answer these questions, we build on the extant literature on organizational transformation, on studies focusing on inertia in IT-based implementations, and on the dynamic capabilities view of the firm. Adopting a multiple case study approach in which we interview higher level executives of IT departments from 27 firms, we present findings and discuss the implications that they create for both research and practice. The rest of the paper is structured as follows. In section 2 we overview the *status* *quo* of research on inertia, stages of IT adoption and diffusion, and dynamic capabilities. In section 3 we then describe the research methodology we employ to answer the questions of this study as well as the data collection process. In section 4 we present the results of the study, and closing with section 5, we discuss the theoretical and practical implications of our study.

Background

Organizational Inertia

Understanding what factors enable or inhibit organizational adoption and diffusion of emerging information technologies (IT) has been a subject of much attention for researchers and practitioners for the last three decades (Karahanna et al. 1999). One of the main assumptions inherit with the adoption of any new IT innovation is that it includes a certain level of organizational transformation to both incorporate IT into operations as well as to improve business efficiency as a result of it (Besson and Rowe 2012). Yet, it is commonly observed that when any transformation is required, organizations are rigid and inert, frequently resulting in the overall failure of the newly adopted IT (Haag 2014). Prior studies in management science and in the information systems literature have examined and identified different forms of inertia, which are usually manifested at a variety of levels and throughout numerous agents (Polites and Karahanna 2012). Nevertheless, despite several studies that look into the role of inertia in a number of contexts and for different types of IT, these is still very limited research on the particularities that big data analytics play, and the inertial forces that can possibly slow down implementation and hinder business value. Even more, there is still scarce research on how such inertial forces hinder the application of big data analytics towards the development of dynamic capabilities. To understand how these forces, emerge and to be able to derive theoretical and practical implications, we start by first surveying the state-of-the-art of existing literature on organizational inertia, especially with regards to IT adoption and diffusion.

Organizational inertia, rigidity, path dependence or stickiness, is a topic that has long been in the center of attention for scholars in the managerial science domain (Vergne and Durand 2011). Inertia represents the downside for stable and reproducible structures that guarantee reliability and accountability of organizations (Kelly and Amburgey 1991). The main problem with inertia is that its existence is usually discernible when the need for change arises, which is mostly evoked by external stimuli such as changes in the market. The process of realigning the organization with the environment therefore requires that the forces of inertia that are present within an organization should be overcome (Besson and Rowe 2012; van de Wetering et al. 2017a). We ground our research on the extant literature in the domain of IT-enabled organizational transformation and management science that identifies five broad forms of inertia (Barnett and Pontikes 2008; Hannan and Freeman 1984; Rowe et al. 2017; Stieglitz et al. 2016). These include negative psychology inertia, socio-cognitive inertia, socio-technical inertia, economic inertia, and political inertia (Besson and Rowe 2012). In the context of IT research, Besson and Rowe (2012 give a clear definition of what inertia is in the face of novel organizational implementation. Specifically, they state that *"inertia is the first level of analysis of organizational transformation in that it characterizes the degree of stickiness of the organization being transformed and defines the effort required to propel IS enabled organizational transformation"*. The authors do mention that identifying the sources of inertia is only one level, the second being process and agency, and the third performance. These levels help distinguish causes of inertia from strategies to overcome them and quantifiable measures to assess their impact on organizational transformation.

Following this distinction between different forms of inertia, the first step of our analysis is to clearly define and understand how the different sources of inertia have been examined in literature and at what level they appear. Negative psychology inertia has been predominantly attributed to group and individual behavior and is based on perceived threat of losing power or even the position that an employee has within the firm. When there is increased uncertainty about the role that individuals or groups have in the face on novel technological deployments negative psychological reactions can arise which biases them towards the current situation (Kim and Kankanhalli 2009). Socio-cognitive inertia is mostly focused on malleability due to path dependencies, habitualization, cognitive inertia and high complexity (Lyytinen and Newman 2008). This type of inertia arises as a result of periods of sustained stability and routinization caused by a stable environment in which there is no need for adaptation, and therefore change processes are not well maintained. Socio-technical inertia on the other hand refers to the dependence on socio-technical capabilities, which arise from the interaction of the social systems and technical system and their joint optimization (Rowe et al. 2017). Economic inertia can appear in the form of commitment to previously implemented IT solutions that do not pay off and create sunk costs, or through transition expenses which make organizations not adopt potentially better alternatives (Haag 2014). Finally, political inertia is caused by vested interests and alliances which may favor that the organization remains committed to a specific type of information technology so that partnerships are not broken. Organizational transformation therefore is a complex process, and the different forms of inertia described above are most likely intertwined and inter-related. Nevertheless, the question is which types should be considered, at what level, and how does the context of big data analytics influence their presence.

While to date there has been no systematic study to examine the forms of inertia in big data analytics implementations, several research studies have reported inhibiting factors during adoption and diffusion (Mikalef et al. 2018c). Mikalef et al. (2017) mention that in some cases economic inertia caused a problem in the adoption of big data analytics. The authors state that top managers were reluctant to make investments in big data analytics, since their perceptions about the cost of such investments in both technical and human resources greatly exceeded the potential value. In addition, they mention that both socio-cognitive and socio-technical issues rose at the group level, where people were reluctant to change their patterns of work and were also afraid of losing their jobs. Similar findings are reported by Janssen et al. (2017), where socio-cognitive inertia can be reduced by implementing governance schemes, which dictate new forms of communication and knowledge exchange. In their study, Vidgen et al. (2017) note that inertial forces impact the implementation of big data projects, and that the presence of the right people that can form data analytics teams and implement processes is critical to success. Similarly, Kamioka and Tapanainen (2014) find that systematic use of big data was influenced by the attitude of users and top management

Adoption Process Model

An important part of the adoption process is the existence of a new technology, particularly when it is posited to be a source of organizational performance gains in fiercely competitive industries. Literature in the domain of information systems has focused on many different types of IT, and examined adoption and diffusion at different levels (Karahanna et al. 1999). One main distinction that is commonly made is between a state of adoption, and that of continued usage (Oliveira and Martins 2011). Studies that deal with adoption, typically look at factors that influence decisions to do so, as well as barriers or conditions that hinder doing so (Baker 2012). On the other hand, literature that looks into the continued usage, usually focuses on the individual and not on firm-level dynamics (Belanche et al. 2014). Nevertheless, in reality there are multiple stages throughout the adoption and diffusion stage within firms. Since we are more interested in looking at the organizational dynamics of the processes, rather than explaining adoption decisions or stages of technical implementation, we follow an adoption process approach to determine the main sources of inertia in big data analytics projects throughout different phases (Mergel and Bretschneider 2013).

The first stage is *intrapreneurship and experimentation*, where the new technology is typically used informally by individuals within the IT department. Users usually have little to no knowledge on the new technology and learn through experimentation, or when the firm decides to invest in some employees with related skills. During this stage, individual experimenters work to gradually diffuse the technology throughout the organization and communicate its value. This stage can be initiated either by employees in the IT department, or by top management which sees the new technology as worth looking into. The second stage is called *order from chaos*, in which different units within the organization gradually become accustomed to the new technology and are invited to participate in activities oriented towards its diffusion. The success of the technology at this stage largely depends on the establishment of formal rules, standards, and governance practices for the deployment and use of the technology. The third and final stage is called *institutionalization* in which the new IT becomes part of the organizational fabric. The existence of governance schemes and rules also allows for the technology to reach a broader set of actors. In this stage it is common that there is a well-defined strategy on how the technology is used firm-wide along with a clear assessment of the expected business value.

While these stages have been clearly defined in literature for different types of technological innovations (Mergel and Bretschneider 2013), in the case of big data they are seldom referenced. One of the downsides of doing so is that firms expect that their investments will pay off before they have been completely assimilated within the organization, and without the presence of a solid strategy and governance for achieving business goals. Having defined these stages allows us to understand the inertial forces that dominate each one, as well how they can be overcome. Nevertheless, it is important to take into account the different processes the comprise dynamic capabilities, and how big data analytics are utilized with the aim to strengthen them. Since the processes of sensing, seizing, and transforming represent a sequence of activities, it is argued that inertial forces will have an important effect on them as well as on their interactions.

Dynamic Capabilities

The Dynamic Capabilities View (DCV) has emerged as one of the most influential theoretical perspectives in the study of strategic management over the past decade (Schilke 2014). Dynamic capabilities have been disaggregated into three general types of functions (sensing, seizing, transforming) oriented toward strategic change. These include *sensing* new opportunities and threats, *seizing* new opportunities through business model design and strategic investments, and *transforming* or reconfiguring existing business models and strategies (Helfat and Raubitschek 2018). Teece (2007 notes that sensing involves analytical systems of scanning, search and exploration activities across markets and technologies. *Seizing* on the other hand entails evaluation of existing and emerging capabilities, and possible investments in relevant designs and technologies that are most likely to achieve marketplace acceptance (Wilden et al. 2013). Finally, *transforming* includes continuous alignment and realignment of specific tangible and intangible assets (Katkalo et al. 2010). While prior empirical research has predominantly examined the outcomes of dynamic capabilities (Drnevich and Kriauciunas 2011; Protogerou et al. 2011), there have been several studies looking into the antecedents of their formation (Capron and Mitchell 2009). Such investigations have looked at antecedents at different levels of analysis, including the organizational (Eisenhardt et al. 2010), individual (Hsu and Sabherwal 2012), and environmental levels (Killen et al. 2012), to isolate factors that either enable or hinder the formation of dynamic capabilities. Nevertheless, there is, to the best of our knowledge, no research that examines the impact of big data and analytics on the creation of dynamic capabilities, and particularly on each of the underlying types of functions (see Table 1).

Table 1. Dynamic Capabilities

	Sensing	**Seizing**	**Transforming**	**Reference**
Definition	*Sensing* is defined as the identification and assessment of opportunities	*Seizing* is defined as the mobilization of resources to address an opportunity and to capture value from doing so	*Transforming* is defined as the continued renewal of the organization	(Teece, 2007)
Value creation	• Positioning for first mover advantage • Determining entry timing	• Leveraging complementary assets • Mobilizing resources to address opportunities	• Managing threats • Changing the business model • Continued renewal	(Katkalo, Pitelis, & Teece, 2010; Teece, 2007)

While there is broad discussion on how big data analytics can help organizations reposition themselves, there is a lack of understanding on how inertial forces that characterize big data analytics project deployments may affect each of the constituent dimensions. Therefore, the aim of this study is to explore the hindering forces of big data analytics implementation in the attainment of dynamic capabilities.

Method

Design

Commencing from the theoretical background and the overview of existing literature on big data-enabled organizational transformation and business value, the present work seeks to understand how the processes of deploying big data analytics within firms is hindered by different forms of inertia, and how these hindering forces impact the formation of dynamic capabilities. We explain how inertia is discernible at different forms and stages throughout the deployment and routinization of big data analytics projects.

We begin our investigation by surveying past literature on the main challenges associated with IT-enabled organizational transformation as well as stages at which deployment of technological solutions is usually divided into. The purpose of this review was to understand the primary reasons IT solutions fail to deliver business value. In addition, since big data analytics ultimately provide value through improved actions based on extracted insight, we investigate the literature on top management decision making and factors that influence their trust in outcomes of big data analytics. Next, we attempt to understand how these notions are relevant to companies that have initiated deployments of big data analytics projects. In addition, we seek to differentiate the different inertia forms that occur in big data-enabled organizational transformation in every stage of diffusion and link these inertial forces to the underlying processes that comprise dynamic capabilities. To do this, this study followed a multiple case-study approach. We selected this methodology since we wanted to observe the phenomenon of how big data analytics are diffused in real business settings, as well as the challenges that are faced when trying to derive value from such investments. The case study methodology is particularly well-suited for investigating such organizational issues (Benbasat et al. 1987). By examining multiple case studies, we are able to gain a better understanding of the tensions that develop between different employees and business units during the implementation of big data analytics. A multiple case study approach also allows us to apply a replication logic in which the cases are treated as a series of experiments that confirm or negate emerging conceptual insights (Battistella et al. 2017). We opted for a deductive multiple case study analysis which was based primarily on interviews with key informants, and secondary on other company-related documents. This selection was grounded on the need to sensitize concepts, and uncover other dimensions that were not so significant in IT-enabled organizational transformation studies (Gregor 2006).

Research Setting

In the selection of companies that were included in our multiple case study approach, we chose among firms that demonstrated somewhat experience with big data analytics. This included companies that had either just recently started experimenting with big data or had invested considerable time and effort in gaining value from big data. Furthermore, we focused mostly on medium to large size companies since the complexity of the projects they were involved in would give us a better understanding of the spectrum of requirements in big data initiatives. Nevertheless, some small and micro firms were also added in our sample since they present unique characteristics and a different set of conditions compared to medium or large firms. Lastly, the firms we selected operated in moderately to highly dynamic markets which necessitated the adoption of big data as a means to remain competitive (Mikalef and Pateli 2017). These companies also faced mimetic pressures to adopt big data since in most cases they were afraid that competitors would overtake them if they did not follow the big data paradigm. Therefore, efforts in developing strong organizational capabilities via means of big data analytics were accelerated. We selected different companies in terms of type of industry within the given boundaries, with the aim of doing an in-depth analysis and to be in place to compare and contrast possible differences (Table 2). The selected firms are considered established in their market in the region of Europe, with most companies being based in Norway, the Netherlands, Italy, and Germany.

Table 2. Profile of firms and respondents

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

Data Collection

While collecting data through interviews is a highly efficient way to gather rich empirical data, there is a limitation of information being subjective since it originates from respondents within firms. Nevertheless, there are several approaches that can be employed which help mitigate and limit any bias that may exist in the data. In this study, we collected data from primary sources, as well as secondary sources to confirm statements and establish robustness. The primary sources consisted of the direct interviews that were conducted with key respondents in firms. The interview procedure focused on their attitudes, beliefs, and opinions regarding their experience with big data initiatives that their firm had undertaken. To avoid any bias in responses, data were collected through semi-structured interviews with managers that were directly involved in the big data initiatives. All interviews were done face-to-face in a conversational style, starting with a discussion about the nature of the business and then following on to the themes of the interview guideline. Overall a semi-structured case study protocol was followed in investigating cases and collecting data in which some main questions and themes were already defined, but were left open based on the responses of the key informants (Yin 2017). All interviews were recorded and later transcribed for analysis. To corroborate statements of the interviewees, published information about the firms in the form of annuals reports, online corporate information, as well as third-party articles were used. Two of the co-authors completed the independent coding of the transcripts in accordance with the defined themes as identified in Table 2. Each coder carefully went through the transcripts independently to find specific factors related to the types of inertia, as well as on biases of managers in making insight-driven decisions and the reasons they do so. This process was repeated until inter-rater reliability of the two coders was greater than 90 percent (Boudreau et al. 2001).

Data Analysis

The empirical data analysis was done through an iterative process of reading, coding, and interpreting the transcribed interviews and observation notes of the 27 case studies (Myers and Newman 2007). At the first stage of our analysis we identified and isolated the main concepts on the basis on the past literature that was discussed in earlier sections. For each case the standardization method was used to quantify these characteristics using an open coding scheme (Yin 2017). This allowed us to cluster primary data in a tabular structure, and through the iterative process identify the relative concepts and notions that were applicable for each case. Collectively, these concepts (Table 3) comprise what is referred to in literature as organizational inertia (Besson and Rowe 2012). The underlying rationale argues that there are several barriers when examining the value of big data projects of firm performance or even during the adoption and diffusion stages which are by different forms of organizational inertia. Some of these forms are discernible at the early-adoption phase, while others appear at the decision-making stage, in which managers for a combination of reasons tend not to adopt the insight that is generated by big data analytics, but rather follow their instinct (Mikalef et al. 2018b). The realized value of a firms' big data analytics capability is therefore considered to be determined by a multitude of factors that influence outcomes.

Table 3. Thematic support for organizational inertia

Inertia Dimensions	Perspective of agent	Level	Supporting References
Economic	Agents are embedded in business models that have their own dynamics arising from resource reallocation between exploitation and exploration processes	Business and sector	Besson and Rowe (2012; Kim and Kankanhalli (2009
Political	Agents are embedded in networks of vested interests that have their own dynamics, especially due to alliances rebuilding time	Business	Besson and Rowe (2012 Jasperson et al. (2002
Socio-cognitive	Agents are embedded in institutions characterized by their stickiness due to norms and values re-enactment	Individual, group, organization and industry	Besson and Rowe (2012; Haag (2014
Negative psychology	Agents are overwhelmed by their negative emotions due to threat perception	Individual and group	Rowe et al. (2017 Polites and Karahanna (2012
Socio-technical	Agents are embedded in socio-technical systems that have their own dynamics, especially due to development time and internal consistency	Group and organization	(Lyytinen and Newman 2008); Rowe et al. (2017

Findings

After transcribing the interviews and assigning them each a thematic tag as those described in Table 3, we started aggregating finding and identifying common patterns. These findings were complemented with the secondary data found from various sources. More specifically, the inertial forces and how they are presented in big data projects are summarized below grouped based on the underlying processes of dynamic capabilities they were oriented towards strengthening. After applying the previously mentioned method on the collected data, we visualized the outcomes in the form of a matrix (Mikalef et al. 2015). In Table 4 the importance of each inertial force is noted and grouped based on the process of dynamic capability. Black circles (●) indicate that the concept at hand was mentioned as being important, whereas a blank circle (○) indicates the absence of it in any interview. Solutions are grouped by dynamic capability process.

Table 4. Clusters of inertial forces for grouped by dynamic capability process

	Sensing			Seizing			Transforming	
	A	**B**	**C**	**D**	**E**	**F**	**G**	**H**
Inertia								
Economic	●	●						
Political								
Socio-cognitive		●		●		●		●
Negative psychology	●		●		●		●	
Socio-technical	●		●	●	●		●	●
Stage of adoption								
Intrapreneurship and experimentation	●							
Order from chaos		●		●	●			
Institutionalization			●			●	●	●

Sensing

Clusters of cases around activities related to sensing are indicated in columns A, B and C. Solution (column) A, represents firms that are in the intrapreneurship and experimentation stage of big data analytics deployments. Companies in this group were piloting early projects in an attempt to identify customer requirements and segment their customer base. A major barrier was the lack of economic resources, negative psychology from employees in the technical departments, and inflexible work practices that revolves around established ways of sensing external conditions. Respondent from C.21 stated the following:

"In the beginning we were not sure if we should go into this (big data). We have seen in the past that these hypes come and go and they are largely promoted by large software companies. When we realized that this is a global phenomenon and that everyone is getting into it we started to look into it…….It was not easy at first, I had everyone working against me, especially from the IT side. The excuses were many, we don't not have time, it is not worth the effort but I realize it was just fear of the unknown."

For firms that where more mature with regard to their deployments of big data analytics, economic barriers as well as socio-cognitive inertia were the main issues when targeting efforts towards sensing activities. This cluster of firms faced difficulties in expanding the practices of big data analytics throughout the organization, and particularly in accessing data that was siloed in other departments. Respondent of C.13 stated the following:

"Once we decided to scale up our efforts and integrate data from the marketing department we faced a problem…regulations within our company were not clear about ownership of data and the our colleagues (marketing department) seemed to not want to lose control of them…there was also the issue of confidentiality and privacy of information and these were not in a clear form…I would say that this really stalled our efforts"

Firms that were highly mature and belonged to the stage of institutionalization however were presented with a different set of inertial forces. Negative psychology by decision makers with regard to the outcomes of analytics, as well as reliance on routinized ways of making decisions were found to be the main inhibiting forces with regard to leveraging big data analytics for sensing opportunities and threats. Specifically, the respondents from C.27 stated the following:

"While we have established big data analytics to be a core part of our business and now conduct analysis of real-time information, there still seems be some skepticism about whether our outcomes are truthful or not….we try to be completely transparent about how things are done but my feeling is that it is not enough to convince management".

Seizing

Activities related to seizing based on big data analytics included real-time process orchestration, allocating resources dynamically, and coming up with solutions based on data-generated insight. Firms that belonged to the maturity stages of order from chaos, and institutionalization were utilizing big data analytics to inform seizing processes. Two clusters (D and E) included firms in the order from chaos stage of maturity, the main issues faced included the unwillingness of other departments to adopt strategies of developing solutions based on data-driven insight. For instance, the respondent from C.14 noted that when it came to develop dynamic pricing policies based on customer segments of analytics, there was much resistance about the effectiveness of doing so. Specifically, he quotes that:

"Although we came up with a dynamic way of offering personalized packages to our consumers, the main argument was that we are very profitable in this way so we risk if we change our methods. I must say that I also lost a bit of faith and was very reluctant in persuading them"

Firms that belonged to the F cluster had imbedded analytics more in their seizing activities. Nevertheless, top level management in a few occasions disregarded outcomes of analytics presented to them in the form of real-time dashboards with KPIs. For instance, respondent from company C.1 stated the following:

"In our company we have developed real-time reporting mechanisms that are really effective aids when making decisions. However, they do not include information that it implicit and difficult to put in numbers…I oftentimes find myself making decisions based on experience and what I see happening in the outside world…in this way I see that analytics have a role but also limits"

Transforming

To ensure that business analytics delivers sustained business value, it is critical that organizations quickly transform their existing mode of operation (organization, process, people, technology) to adapt to the changing competitive landscape. Transforming activities include fundamentally reshaping marketing and operational approaches, developing new business models, and fostering a culture of data-driven decision-making. In activities of transforming we only found firms that were in the stages of institutionalization, with two different clusters emerging. In cluster G, there was negative psychology since these firms were in the process of transforming their business models based on big data analytics, accompanied by a presence of strong socio-technical inertia. For example, C.22 were piloting a new business model which developed personalized advertisements based on use of their existing mobile-phone application. The personalized advertisement platform was then launched as a stand-alone application, however there was doubt from top management about the success that it could have since the firm was venturing into unknown territories. The respondents noted the following:

"When we finally decided to launch our new service, there wasn't much willingness to invest resources as it was not seen as a core activity of our business…I think we all realized that we need to innovate and transform our business model, but we were held back by reluctance and fear of the unknown"

The second cluster of companies (H) presented a different set of inertial forces, with socio-technical and socio-cognitive barriers being the main inhibitors of transforming. The respondent from C.25 specifically commented on the choice to fully automatize customer support through the use of AI. Although the pilot technology was tested and would largely transform the ways customer queries and complaints were handled, there was a reluctance regarding the effect that such a transition could have on customer satisfaction. Specifically, the respondent noted that:

"It is quite different to implement new solutions in the safe environment of the organizational boundaries compared to real life situations…there was much skepticism about going forward with this and we had extensive discussion about how we could implement the solution of automated customer query handling without incurring any problems…it took a leap of faith and a well-structured transition plan in order to gradually change the way we deal with complaints"

Discussion

In the current study we have examined how inertia in big data projects influence their success and we specifically looked at how the underlying processes that comprise dynamic capabilities are affected. We built on prior literature which distinguishes between five different types of inertia; economic, political, socio-cognitive, negative psychology, and socio-technical. Specifically, we examined how these forces of inertia are manifested in contemporary organizations through 27 case studies and in different stages of adoption and diffusion. To do so, we followed a process adoption model that identifies three stages of assimilation of new technologies in organizational fabric. Our results show that value from big data investments, and even actual implementation, can be hindered by multiple factors and at multiple levels which need to be considered during the planning phase. To the best of our knowledge this is one of the first attempts to isolate these inhibiting forces and provide suggestions on which future research can build. Managers can also benefit from the outcomes of this study, since it helps develop strategies for adopting and diffusing their big data investments or anticipating inertial forces that will occur at later stages.

Implications for Research

From a research perspective the contribution of this research is that even in the presence of all necessary big data analytics resources, there are multiple ways in which a business value can be hindered. This raises the question of how these obstacles can be overcome. While there is a stream of research into the issues of information governance (Mikalef et al. 2018a; Tallon 2013) these studies primarily focus on the issue of how to handle data and how to appropriate decision making authority in relation to the data itself. There still seems to be an absence of governance schemes that follow a holistic perspective and include management and organization of all resources, including human and intangible ones (van de Wetering et al. 2017b). In addition, how firms should handle individual, group and industry-level dynamics is a topic that is hardly touched upon. The process view of big data analytics adoption is also a topic that is very scarcely discussed. Most research to date assumes that by investing in an appropriate mix of resources, companies will be able to derive business value from big data analytics. Previous technological innovations, and their implementation in the organizational context show that this is not the case. Our findings replicate these results, and show specifically what tensions rise, at what levels, and at what forms when planning big data adoption. Furthermore, we add to literature on the dynamic capabilities view of the firm by showing how big data analytics may be impeded in enhancing their formation as suggested by prior literature. Specifically, we show that while big data analytics may have a positive effect on each of the underlying dimensions that comprise dynamic capabilities, this effect has to be considered under the various inertial forces that hinders their strengthening. This perspective is in line with the path dependency literature which described how dynamic capabilities emerge and what barriers impede their formation.

Implications for Management

From a managerial point of view, the results of this study outline strategies that can be followed to mitigate the effects of the different types of inertia. Our findings indicate that inertia can be present at many phases of adoption and diffusion, so action need to be taken throughout projects. It is critical to consider the socio-technical challenges that these technologies create for middle-level managers and clearly understand how their decision-making is influenced or not by insight generated by big data. In addition, it is important to develop strategies so that the whole organization adopts a data-driven logic, and that a common understanding and language is established. With regards to the IT department, educational seminars and incremental projects seem to be the way to limit negative psychology barriers. Also, providing a clear sense of direction as to what kind of analytics are to be performed on what data is of paramount importance. It is commonly observed that many companies delve into the hype of big data without having a clear vision of what they want to achieve. By clearly defining the three main stages of adoption, a time-based plan can also be deployed in which the barriers in each can be easily predicted, and contingency plans can be formed to overcome them.

Limitations

While this research helps to uncover forces of inertia and the levels at which they present themselves, it does not come without limitations. First, we looked at companies that have adopted big data, a more complete approach would be to look at what conditions cause other firms to not opt for big data. Second, while we briefly touched on the issue of middle-level managers not following insight generated from big data, it is important to understand in more detail the decision-making processes that underlie their reasoning. Also, the actions that are taken in response to these insights are seldom put into question. This is a future are which should be examined since the value of big data cannot be clearly documented in the absence of knowledge about strategic or operational choices.

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