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A Stage Model for Uncovering Inertia in Big Data Analytics Adoption

Completed Research Paper

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Abstract

Big data and analytics have been credited with being a revolution that will radically transform the way firms do business. Nevertheless, the process of adopting and diffusing big data analytics, as well as actions taken in response to generated insight, require organizational transformation. Yet, as with any form of organizational transformation, there are multiple inhibiting factors that threaten successful change. The purpose of this study is to examine the inertial forces that can hamper the value of big data analytics throughout this process. We draw on a multiple case study approach of 27 firms to examine this question. Building on a stage model of adoption, our findings suggest that inertia is present in different forms, including economic, political, socio-cognitive, negative psychology, and socio-technical. The ways in which firms attempt to mitigate these forces of inertia is elaborated on, and best practices are presented. We conclude the paper by discussing the implications that these findings have for both research and practice.

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

Introduction

Despite big data analytics being in the spotlight of attention by researchers and practitioners in the last few years, until now there has been a very limited focus on what forces can potentially hinder the potential business value that these investments can deliver. Most studies have emphasized on the necessary investments that must be made to derive business value (Gupta and George 2016), but the process from making the decision to adopt such technologies, 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). Nevertheless, 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.

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; Vidgen et al. 2017). Nevertheless, to date there is a very limited understanding on how these should be implemented and what factors may inhibit successful deployment or even adoption. In this respect, there is not much attention on the processes of big data adoption and implementation. 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; 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 innovation suggest that they emerge in different stages of diffusion and assimilation (Limayem et al. 2003).

This study builds on the aforementioned gaps, and attempts to understand how inertial forces hinder the potential value of big data analytics. 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. Doing so enables us to detect the different forms of inertia, and the stages at which they emerge. Hence, this research is driven by the following research question which helps guide our investigation:

> *How is inertia present in big data projects? At what stages do inertial forces appear and at what levels?*

To answer these questions, we build on the extant literature on organizational transformation and on studies focusing on inertia in IT-based implementations. Following 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 big data and business value, inertia, and stages of IT adoption and diffusion. Section 3 then describes 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

Big Data and Business Value

Big data analytics is widely regarded as the next frontier of improving business performance due to its high operational and strategic potential (Brown et al. 2011). The literature defined big data analytics as "a new generation of technologies and architectures, designed to economically extract value from very large volumes of a wide variety of data, by enabling high velocity capture, discovery and/or analysis" (Mikalef et al. 2017b). While most claims on the value of big data analytics are anecdotal, the emerging literature has documented a positive relationship between the decision to invest in firm-wide deployment of big data analytics and performance (Gupta and George 2016). Big data analytics enable firms to make sense of vast amounts of data and reconfigure their strategies based on trends that are observed in their competitive environment (Chen et al. 2012). The importance of big data analytics is evident from the increasing investments made from firms, and particularly those working in complex and fast-paced environments (Wang et al. 2016). Managers nowadays are relying ever more on big data analytics to inform their decision-making and direct future strategic initiatives (Constantiou and Kallinikos 2015). The value of investing in big data analytics is clearly reflected in a recent article by

Liu (2014, who notes that big data analytics constitutes a major differentiator between high-performing and low-performing firms, as it enables firms to be more proactive and swift in identifying new business opportunities. Similar results are found in a study by Kamioka and Tapanainen (2014) in which systematic and extended use of big data analytics leads to increased competitiveness. Additionally, the study reports that big data analytics have the potential to decrease customer acquisition costs by 47% and enhance revenues by about 8%. A report by MIT Sloan Management Review shows that companies that are leaders in the adoption of big data analytics are much more likely to produce new products and services compared to those that are laggards (Ransbotham and Kiron 2017). Nevertheless, the value that firms realize from big data investments, is highly contingent upon the idiosyncratic capabilities that they develop in deriving meaningful insight (Janssen et al. 2017).

Organizational Inertia

Understanding what factors enable or inhibit organizational adoption and diffusion of emerging information technologies (IT) has long been a subject of much attention for researchers and practitioners (Karahanna et al. 1999). The main assumption 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, in spite of several studies that look into the role of inertia in a number of contexts and for different types of IT, these is still scarce research on the particularities that big data analytics play, and the inertial forces that can possibly slow down implementation and hinder business value. To understand these and derive theoretical and practical implications, we start by first surveying the status quo of existing literature on organizational inertia, especially with regards to IT adoption and diffusion.

Organizational inertia, rigidity or stickiness, is a topic that has long been in the center of attention for scholars in the managerial science domain. Inertia represents the downside for stabile 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 to be overcome (Besson and Rowe 2012; van de Wetering et al. 2017a). We ground our study 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 segregation, 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 are present. Negative psychology inertia has been predominantly attributed to group and individual behavior, and is based on threat perceptions of losing power or even employee position within the firm. Uncertainty about the role of individuals or groups in the face on novel techno-logical deployments thus causes negative psychological reactions which biases them towards the current situation (Kim and Kankanhalli 2009). Socio-cognitive inertia is focused mostly on malleability due to path dependencies, habitualization, cognitive inertia and high complexity (Lyytinen and Newman 2008). These forms of inertia arise due to 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 may be apparent 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 dimensions 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. 2018b). Mikalef et al. (2017a) 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 fierce 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 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 called *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.

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 as well as other barriers. We explain how inertia is discernible at different forms and stages throughout the deployment and routinization of big data analytics projects. Specifically, we base our investigation on the following research question:

What form of inertia are detectable during the process of big data-driven organizational transformation? At which stages are they detectable and how can they be over-come?

We began 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 looked into the literature on top management decision making and factors that influence their trust in outcomes of big data analytics. Next, we attempted to understand how these notions are relevant to companies that have initiated deployments of big data analytics projects. In addition, we sought to differentiate the different inertia forms that occur in big data-enabled organizational transformation in every stage of diffusion. 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 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, as well as the causes of non-use of generated insight by top managers. 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 1). 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 1. 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 trhough 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 2) 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. 2017b). 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 2. 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 2, 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 stage in which each firm is in its adoption and assimilation of big data analytics.

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 3 the importance of each inertial force is noted and grouped based on the stage of the project and other contextual factors. 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

Table 3 Clusters of inertial forces for different stages of big data analytics adoption and implementation

	Stage 1			Stage 2		Stage 3	
	A	**B**	**C**	**D**	**E**	**F**	**G**
Inertia							
Economic	●			●			
Political	○		●	○			
Socio-cognitive		●			●		●
Negative psychology	●	●	●	●	●	●	
Socio-technical						●	●
Context							
SME	●			●			
Large		●	●		●	●	●

Stage 1. Intrapreneurship and experimentation

In the first stage we had three different combination of inertial forces (A, B and C). Solution A describes firms that are in the SME size-class. These projects were severely hampered by a lack of economic resources, in which top management and the board of directors had doubts about the value of big data analytics in their operations. In addition, there was severe resistance from employees in the IT department about big data implementations since they didn't feel they had the skills to cope with these new technologies and feared being replaced by top management. Specifically, the 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."

Solutions B and C correspond to large firms, in which a different combination of inertial forces took place. In both cases negative psychology of the IT department was a major issue of delay, however, in large companies it was overcome easier due to a strong fear of been replaced. In companies tha belonged in the B category, socio-cognitive inertia was a major concern since for the first time they were faced with the issue of collecting data from different departments. This caused tensions to rise between employees of different departments, and confusions to the different mental modes, use of language, and objectives. The representative of the C.19 stated the following.

"When we had a meeting with the risk assessment team and tried to explain them what we would like to try to do there was a lot of confusion. I don't think they understood what kind of data we were looking

for and were unaware of the types of analyses we were planning to do. This caused a bit of reluctance from their side which was eventually overcome when the consulting firm intervened"

In companies of group C, political inertia was a major cause of concern since these companies were mostly involved in alliances or were locked-in by vendor restrictions leading them to not have access to the data they wanted to. One example is from the IT manager of a software company who had secured a deal with a hospital to perform analytics and develop a novel service for patients. While there were initial agreements between the hospital management and the software company, the project was forced to end early since the data they needed to access were inaccessible due to restriction in the terms of use of the information systems of a third vendor. In order to maintain a good relationship with the vendor, the hospital decided that the project was not of much value and therefore it was not worth creating conflict over it.

Stage 2. Order from chaos

In this stage of adoption, companies faced a different set of inertial forces which required adaptation in decision-making and the implementation of firm-wide policies to ensure project success. Companies of group D, which were in the SME size-class, continued to present the same of inertial forces. This time however the economic inertia had to do mostly with hiring employees that had expertise in a specific type of analytics. Such companies faced the problem that it was hard to decide on what areas they wanted to focus on, and what type of insight would be valuable for them to generate. This caused indecisiveness in terms of the staff that needed to be employed and severely delayed big data assimilation. Respondent from company C.13 states.

"We had a problem deciding what we would like to do with big data. I think everyone had their own idea and there was no way to prioritize or decide. Looking at it now I think the main problem was a lack of a clear structure with regards to decision making when it comes to big data. In the end we made up a short-term plan, but quickly realized that the biggest problem would be to find someone that can execute it. There is a tremendous scarcity of skilled labor in the market. This is something universities need to address fast!"

This problem however was not found in large firms where the presence of socio-cognitive inertia characterized stage 2 of adoption and diffusion. The main problem noted in this cluster of companies was a lack of well-defined practices to allow for communication and collaboration between different departments in the roll-out phase. When more technically-oriented employees were put into a position to explain the objectives of big data analytics projects, there was confusion by other departments. In addition, the move towards being more data-driven meant that all departments need to be knowledgeable about analytics and big data. The use of liaison person with a good technical and domain specific background helped alleviate such problems. In addition, conducting regular meetings with representatives of each department was seen as a positive move in creating a common understanding, establishing a language which was jargon free and easily comprehendible, and the formation of a group that had decision making powers in respect to big data analytics were successful in reducing rigidity of departments.

Stage 3. Institutionalization

During the final stage of adoption and assimilation of big data analytics into organizations, two main types of organizational inertia combination continued to exist. While they were present to a much lesser extent, there still existed hindering business value. In both cases negative psychology still continued to exert a strong influence, however, at a different level. The employees that showed signs of negative psychology were not top and middle level management, who frequently discarded the insights that were generated by big data analytics. It was frequently noted by respondents that they didn't have complete faith in the insight that was generated, due to many factors that played an important role during the insight generation process. From the quality of the data, to the techniques used to cleanse them and analyze them, as well as the algorithms and statistical tools used to derive insights. Some even replied that the completeness of the data was not to an extent to which it could replace manager knowledge and instinct.

For companies of group F, a major issue was the presence of socio-technical inertia. This form of inertia manifested itself through resistance of middle-level managers in decision making and insight generation. Typically, they would inform their decision based on conventional business intelligence methods. However, the use of unstructured data that came from a number of different sources created a major distrust towards the outcomes of the analysis. A respondent from company C.27 stated the following.

"We had some serious problems at the later stages of our big data initiative. We tried to combine our data with external sources and weather data. We were hoping that this would give us an edge on detecting faults, but our maintenance department didn't even want to consider our analysis. They were convinced that the way they did things was fine, so nothing needed to be changed. They were also very skeptical about using data that had no quality control."

Resolving this issue required top management to intervene through a number of ways. The most important of which was to create regular workshops in which the whole process of collecting, storing and analyzing data was discussed with all employees. This allowed them to have their own saying and to develop trust and a sense of co-ownership to insight. The last group of companies, G, where top managers didn't follow the recommendation that insight produced. Their main issue was that they believed that their instinct could not be replaced by analytics. This form of inertia was particularly difficult to overcome, since it dependent to a large extent on the individual and how exactly they make decisions.

Discussion

In the current study we have examined how inertia in big data projects influence their success. 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.

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 can these obstacles 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.

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.

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 actually adopt 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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