Big Data enabled organizational transformation: The effect of inertia in adoption and diffusion

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Abstract. Big data and analytics have been credited with being a revolution that will radically transform the way firms operate and conduct business. Nevertheless, the process of adopting and diffusing big data analytics, as well as actions taken in response to generated insight, necessitate organizational transformation. 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. 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

1 Introduction

While big data analytics have been in the spotlight of attention by researchers and practitioners in the last few years, to date there has been limited attention on what forces can potentially hinder the potential business value that these investments can deliver. Much research has focused on the necessary investments that must be made to derive business value [1], but the process from making the decision to adopt such technologies, up to turning insight into action is seldom discussed, particularly with respect to inertia. 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 [2]. 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 [3].

While big data literature has documented the importance that organizational learning and a data-driven culture have on overall project success [4], there is to date 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 to date have attempted to provide a narrative on how big data can produce value [5], or even empirically show an association between investments and performance measures [1, 6]. 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. The purpose of this study is therefore to attempt to understand how inertial forces in these levels hinder the potential value of big data analytics. By doing so, it is possible to isolate key success factors of implementation and help guide practitioners in developing strategies for adoption and deployment [7].

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. We isolate five key forms of inertia, namely, *economic, political, socio-cognitive, negative psychology, and socio-technical* and examine how each of these is present in big data analytics projects in firms. 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.

2 Big Data Analytics 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 [8]. 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" [9]. 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 [1]. 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 [10]. 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 [11]. Managers nowadays are relying ever more on big data analytics to inform their decision-making and direct future strategic initiatives [12]. The value of investing in big data analytics is clearly reflected in a recent article by Liu [13], 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. 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 [14]. Nevertheless, the value that firms realize from big data investments, is highly contingent upon the idiosyncratic capabilities that they develop in deriving meaningful insight [15, 16].

3 Organizational Inertia and Decision Making

Understanding what factors facilitate or inhibit organizational adoption and diffusion of emerging information technologies (IT) has long been a primary concern for researchers and practitioners [17]. The main premise associated with adoption of any new IT innovation is that it entails a level of organizational transformation to both incorporate IT into operations as well as improve business performance as a result of it [18]. Nevertheless, it is frequently noted that when transformation is required, organizations are rigid and inert, resulting in the overall failure of the newly adopted IT [19]. Past studies in management science and in the information systems literature have examined and isolated different forms of inertia manifested at different levels and throughout numerous agents [20]. Nevertheless, despite several studies examining the effect of inertia on different contexts and types of IT, these is very limited research on the role 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 first start by surveying the status quo of existing literature on organizational inertia, particularly with regards to IT adoption and diffusion.

Organizational inertia is a subject that has long been in the center of attention for scholars in the managerial science domain. Inertia represents the price for stabile and reproducible structures that guarantee the derided reliability and accountability of organizations [21]. Nevertheless, the presence of inertia is usually discernible in the need for change and is distinguishable when external stimuli demands so. The process of realigning the organization with the environment therefore requires that the forces of inertia that are present within an organization need to be overcome [18]. We build on the extant literature in the domain of IT-enabled organizational transformation and management science and identify five broad types of inertia [18, 22-24]. These include negative psychology inertia, socio-cognitive inertia, socio-technical inertia, economic inertia, and political inertia [18]. In the context of IT research, Besson and Rowe [18] provide a clear definition of what inertia represents 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".* They do however 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.

The first step however 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 their position. Uncertainty about the role of individuals or groups in the face of novel technological deployments thus causes negative psychological reactions which biases them towards the *status quo* [25]. Socio-cognitive inertia emphasize mostly on malleability due to path dependencies, habitualization, cognitive inertia and high complexity [26]. These forms of inertia arise due to periods of sustained stability and routinization caused by a stable environment. 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 [27]. Economic inertia may be present in the form of commitment to previously implemented IT solutions that do not pay off and create sunk costs, or through transition expenses which cause organizations to not adopt potentially better alternatives [19]. 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.

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, Framnes, Danielsen, Krogstie and Olsen [28] mention that in some cases economic inertia caused a problem in the adoption of big data analytics. The authors state that top managers in some cases 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, van der Voort and Wahyudi [15], where socio-cognitive inertia can be reduced by implementing governance schemes [29], which dictate new forms of communication and knowledge exchange. In their study, Vidgen, Shaw and Grant [4] 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.

4 Research Method

4.1 Design

Beginning from the theoretical background and the overview of existing literature on big data-enabled organizational transformation and business value, the present work aims to understand how the processes of deploying big data analytics within companies is hindered by different forms of inertia as well as decision making barriers by top managers in the process of decision making. We explain how inertia is presented 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 hindrances are detectable during the process of big data-driven organizational transformation? At which stages are they detectable and how can they be overcome?

We started our investigation by surveying past literature on the main challenges associated with IT-enabled organizational transformation. The purpose of this review was to understand the primary reasons IT solutions fail to deliver business value. Next, we attempted to understand how these notions are relevant to companies that have initiated deployments of big data analytics projects. To do this, this study followed a multiple case-study approach. The case study methodology is particularly well-suited for investigating organizational issues [30]. Through multiple case studies, we are able to gain a better understanding of the frictions that are created 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. Through a multiple case study approach, it is also possible to enable a replication logic in which the cases are treated as a series of experiments that confirm or negate emerging conceptual insights [31]. We chose a deductive multiple case study analysis 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 [32].

4.2 Research Setting

For the sample of companies that are included in our multiple case study approach, we selected firms that demonstrated somewhat experience with big data analytics. This included companies that had either just recently started or had invested considerable time and effort in gaining value from big data. In addition, 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. Lastly, the firms we selected operated in competitive and highly dynamic markets which necessitated the adoption of big data as a means to remain competitive. 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 European region, with most companies being based in Norway, the Netherlands, Italy, and Germany.

Table 1. Profile of firms and respondents

Code	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)

4.3 Data Collection

In this study, we collected data from primary sources, as well as secondary sources to confirm statements and establish robustness. The primary sources were the direct interviews that were conducted with key respondents in firms. The interview focused on their attitudes, beliefs, and opinions regarding their experience with big data initiatives that their firm had undertaken. All interviews were conducted face-to-face in a conversational style, opening with a discussion on the nature of the business and then proceeding on to the themes of the interview guideline. Overall a semi-structured case study protocol was followed in investigating cases and collecting data [33]. Discussion were recorded and then transcribed for analysis. 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 read 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 [34].

4.4 Data Analysis

The empirical analysis was performed by an iterative process of reading, coding, and interpreting the transcribed interviews and observation notes of the 27 case studies [35]. At a first stage we identified and isolated a large number of concepts based on the literature that was discussed in earlier sections. For each case the standardization method was used to quantify these characteristics using an open coding scheme [33]. 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 [18]. The underlying logic suggests that there are multiple barriers when examining the value of big data projects of firm performance, some of which are caused due to organizational inertia and are discernible at different stages of implementation, 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 [9]. The effect of a firms' big data analytics capability on performance is therefore considered to be mediated and moderated by numerous factors that appear at different stages of the implementation process.

Table 2. Thematic support for organizational inertia

Inertia Dimensions	Perspective of agent	Level	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 [18] Kim and Kankanhalli [25]
Political	Agents are embedded in networks of vested interests that have their own dynamics, especially due to alliances rebuilding time	Business	Besson and Rowe [18]
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 [18] Haag [19]
Negative psychology	Agents are overwhelmed by their negative emotions due to threat perception	Individual and group	Besson and Rowe [18] Polites and Karahanna [20]

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	Besson and Rowe [18] Lyytinen and Newman [26]

5 Results

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. More specifically, the inertial forces and how they are presented in big data projects are summarized below.

5.1 Economic Inertia

Economic inertia was a very prominent theme amongst most of the companies, especially those that were not multi-national firms or had major slack resources, such as micro, small, and medium enterprises. For large conglomerate companies, scarcity of economic resources towards the implementation of big data projects was not an issue. Specifically, in non-large companies', economic inertia was present from the top management and board of directors, who had doubts about the value of big data analytics in their operations. The respondents from companies C.13 and C.24 respectively made the following comments.

"For us the value of big data analytics was not clear. We did not want to invest in a fashion just because everyone else is doing it. These technologies are expensive because we need personnel that we currently do not have."

"The management was very skeptical about if we should go into big data. Our competitors were doing that and it meant that we had to follow so that we are not left behind. We tried to experiment in the beginning with some internal resources but then we understood that we have to invest more. This was a hard decision to make and perhaps we delayed a bit on this (adopting big data)"

Similar quotes were made by several other executives, showcasing that economic inertia are a major inhibiting factor of big data adoption and deployment. A major inhibitor that leads to this is the unclear link between big data investments and business value. On the other hand, competitive pressures seem to be driving mimetic behaviors in companies mitigating the effects of economic inertia.

5.2 Political Inertia

Political inertia was detected in several firms that had formed partnerships with other private and public organizations. Specifically, in C.5 the manager made some remarks about lock-in effects that vendors of information systems led them to. The IT department of C.5 wanted to utilize data of their own in combination with some from a partner of a hospital. The vendor of the partner hospital information systems didn't allow for the extraction and use of data in third party analytics tools, and promoted his company's analytics tools. The top management of the hospital wanted to retain good relationships with the vendor of their information systems because they formed the backbone of operations for different departments, so the partnership between the two entities was forced to collapse. Similar phenomena were observed especially in the case of private-public alliances, were public bodies are trapped by vested interests.

5.3 Socio-Cognitive Inertia

Socio-cognitive inertia were found to be a problem in most of the companies that were examined. In most of the cases, big data implementation meant that data from different departments needed to be gathered. This entailed that a detailed account of what data were available should be initiated, and in many cases new processes needed to be put into place to collect data. Typically, the IT department was responsible for starting this process, and had to explain to various other siloed departments their goals, ways of realizing them, and what their role would be. The different mental modes, use of language, and objectives caused conflicts that threatened and even greatly delayed big data implementation projects. An example of this is evident through the comments of respondent of C.10.

"I think we had some major issues when we went into the marketing department and asked them to talk to us about how they gather data on customer preferences based on advertisement campaigns. We understood that they didn't have any feedback mechanism in place to evaluate the success or failure of what they did. This meant that somehow, they had to track the feelings and attitudes of consumers. I think that we also confused them about the data we were looking to collect, this confusion also led to a bit of tension"

Similar examples were found in several companies working external partners such as universities, public bodies, and other companies, as well as in firms that have highly siloed business units. We found that in many cases, consulting firms were brought in to resolve this issue and act as a mediating agent. They tried to create a common understanding of the objectives of the big data projects, and bring representatives from each business unit to the table so that cognitive structures can be in alignment.

5.4 Negative psychology

Negative psychology was again observed mostly in small and medium firms, where the IT department comprised of a small number of employees. Primarily, it was found in personnel that had been actively employed for many years, in contrast to those that had recently graduated. These employees feared that the introduction of big data analytics and the corresponding technologies and tools for analyzing and visualizing data would render their skills as non-significant. Specifically, the respondent from C.8 stated the following.

"When I told the group that we should start to think about what we can do with the data in the company there was a cold silence. They initially objected saying that there would be not much value in doing so and that it was just a waste of time. Others said

that they didn't have enough time to engage in this process since it would take a lot of time to learn how these technologies worked. I realized that deep inside they feared that the move to big data would require for them to learn new stuff, or even mean that the could lose their jobs if they didn't manage to adapt"

We saw that the way many IT managers handled this issue was by providing their division with small challenges, and incrementally growing projects. Also, they assigned a few hours a week where they had the freedom to experiment with big data tools. This allowed them to try out these novel tools at their own pace, without the fear of time-pressure to deliver results. I

5.5 Socio-technical

In terms of socio-technical inertia, it was observed that in many cases middle-level managers exerted behaviors that stalled the implementation of big data projects. Their primary fear was that decision-making would now reside in insight from analytics, therefore replacing them. In many occasions this fear manifested itself as a distrust towards the value of big data analytics, and general tendency to downplay the significance of big data in operations. Despite the clear directive of top management to diffuse big data analytics into operations, in many circumstances middle-level managers would not invest time in clear implementation strategies leaving the IT department with a bleak understanding of how they should proceed. The respondent from C.6 states the following.

"When we made the decision to start working with big data we were happy. Then after some time we were not sure what we should do with it. We presented some examples to management but they didn't take them much into account. We then realized that they prefer to make decisions based on their own knowledge, and didn't trust the process we were following, or even, felt like it may replace them. It was quite discouraging to work on something that is not applied"

Typically, these issues were resolved by a strong top management vision and leadership. In addition, training seminars for middle-level managers on the value of big data and their role were regarded as very beneficial in overall success.

6 Discussion

In the current study we have examined how inertia during the implementation and deployment phases of big data projects influence their success. Following the literature which distinguishes between economic, political, socio-cognitive, negative psychology, and socio-technical, we looked at how these forces of inertia are manifested in contemporary organizations through 27 case studies. 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 and managers can develop strategies for adopting and diffusing their big data investments.

From a research perspective the major finding 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 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. In addition, how firms should handle individual, group and industry-level dynamics is a topic that is hardly touched upon.

From a managerial point of view, the outcomes 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.

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 area 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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