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Building dynamic capabilities by leveraging big data analytics: The role of organizational inertia

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ABSTRACT

Although big data analytics have been claimed to revolutionize the way firms operate and do business, there is a striking lack of knowledge about how organizations should adopt and routinize such technologies to support their strategic objectives. The aim of this research is to explore how different inertial forces during deployments of big data analytics hinder the emergence of dynamic capabilities. To do so, we follow a multiple-case study design approach of 27 European firms and examine the different forms of inertia that materialize during big data analytics diffusion. The findings contribute to the growing body of knowledge on how big data analytics can be leveraged effectively to enable and strengthen a firm's dynamic capabilities. By disaggregating dynamic capabilities into the underlying capabilities of sensing, seizing and transforming, findings indicate that different combinations of organizational inertia including economic, political, socio-cognitive, negative psychology, and socio-technical hamper the formation of each type of capability.

1. Introduction

Big data analytics – that is, the tools and processes applied to large and complex datasets to obtain actionable insights – has been a central topic of discussion for researchers and practitioners for almost a decade now [1,2]. Most empirical research to date has examined the necessary investments that firms must make, or the complementary resources and processes that should be developed in order to drive a business value from such investments [3–5]. While highlighting the core resources when deploying big data analytics is a crucial first step, it does not answer the question of how analytics are deployed and linked to strategy, and especially what aspects during this process can potentially impede value creation [6]. This is surprising since one of the core assumptions of using big data analytics in the organizational setting is that such technologies can help generate insights that can transform the strategic direction of firms before competitors [7]. Subsequently, this entails organizational transformation at multiple levels, which is subject to inertia and other forces of resistance [8]. These inertial forces have been documented in past research within the information systems domain, to have detrimental effects on the business value of technology investments, and can even be the root cause of project failure [9].

Within the body of big data analytics literature, there has been an abundance of research highlighting key resources in generating value from such investments [10–12]. Yet, there is to date a lack of empirical work exploring how different forms of inertial forces may potentially hinder successful deployments and strategic value generation. Recent empirical studies have worked toward the identification of barriers of adoption in big data analytics projects [13], and understanding how organizational actions contribute to actualizing big data analytics affordances and organizational objectives [5,14,15]. While these studies shed some light on the affordances that big data analytics offer, there has been significantly less focus on the strategic value realization of big data analytics [16,17]. In this direction, some studies have demonstrated that structured adoption of big data analytics can positively impact a firms dynamic capabilities, which are posited as being the primary source of sustained performance gains in turbulent and fast-paced environments [6,7]. In his seminal paper, Teece [18] describes that dynamic capabilities can be decomposed into the capabilities of *sensing*, *seizing*, and *transforming*, which jointly contribute toward enabling firms to achieve superior and sustained performance.

While dynamic capabilities are well defined in the management literature, there is still a lack of understanding of the inertial forces that come into play when attempting to leverage big data analytics to strengthen them. To date, research has attempted to provide a narrative

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on how big data analytics can create business value when leveraged appropriately [19], or even empirically show an association between investments in big data analytics and performance measures [4,6,7, 20–24]. Several recent commentaries and editorials have highlighted the need to explore the inertial forces that work against the attainment of such strategic objectives at different phases of deployment of big data analytics [16,17]. Understanding how inertial forces emerge is also of high importance for practitioners who are faced with a number of hurdles at the individual, group, and organizational levels, which need to be overcome in order to derive strategic value from their investments [25, 26]. Despite the general assumption that such barriers mainly exist during the early stages of big data analytics diffusion, several practice-based reports and prior studies on other technological innovations suggest that hindering forces emerge in different stages of deployments [27,28].

The aim of this study is to build on the above-mentioned gaps and to understand how inertial forces hinder the strategic value realization of big data analytics at the organizational level. More specifically, we examine the role of big data analytics in the formation of dynamic capabilities and try to isolate the inertial forces that emerge during different phases of diffusion. In doing this, we build on the 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* as defined by Besson and Rowe [9]. In sequence, we proceed to explain the main stages of diffusion of novel technologies, which include *intrapreneurship and experimentation*, *coordinated chaos*, and *institutionalization* [29]. The stages of diffusion and the types of inertial forces are then mapped onto the three underlying pillars of dynamic capabilities, i.e. *sensing*, *seizing*, and *transforming*. Thus, we are able to detect the different forms of inertia as well as the stages during which they materialize.

The outcomes of the study have important theoretical and practical implications. From a theoretical point of view, the results highlight how inertial forces can cancel out positive strategic effects of novel technologies, through the well-established theoretical lens of dynamic capabilities. Most empirical studies so far have adopted a positivist perspective when considering the value generating mechanisms of big data analytics [17]. This is in stark contrast with the less frequently used interpretivist approaches that consider the responses and reactions of human agents in relation to the introduction of new digital technologies [30]. The outcomes of this research also generate some important implications for practice, as they enable managers to understand how big data analytics deployments relate to their firm's strategy, and at which levels inhibiting forces may emerge. Several practice-based studies have indicated that many companies fail to realize value from their big data analytics investments due to negative psychology of managers to implement these new technologies, or because of unwillingness of departments to collaborate and open up data silos [31]. One of the main shortcomings of existing studies is that they do not provide managers with sufficient guidance about the obstacles they are likely to face during the different stages of deployment. Hence, the following research question guides our investigation:

> *RQ*: *How do inertial forces during the different stages of big data analytics diffusion affect a firm's dynamic capabilities?*

Grounded on 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 *state-of-the-art* research on organizational inertia and the stages of IT diffusion and routinization. We also survey the latest research on big data analytics and business value, and briefly describe the dynamic capabilities perspective. Next, in Section 3, we introduce the research methodology, as well as the data collection process and the selected cases. In Section 4, we present the results of the study, which are sub-divided based on the underlying dimensions that comprise dynamic capabilities: sensing, seizing and transforming. In closing, in Section 5, we discuss the theoretical and practical implications of our study and highlight some core limitations and ways future research can tackle them.

2. Background

2.1. Organizational inertia

The study of identifying what factors enable or inhibit organizational diffusion of emerging and novel information technologies (IT) has been a subject of considerable attention for researchers and practitioners for more than three decades [32]. One of the main assumptions inherit with the deployment of any new IT innovation is that it includes a certain level of organizational transformation to both incorporate IT into operations and improve business efficiency as a result of it [9]. Nevertheless, it is routinely observed that when any form of transformation is required, organizations are rigid and inert, presenting multiple forces of resistance and, in many cases, resulting in the overall failure of the newly adopted IT [33]. Past research in the domain of management science and information systems literature has explored and distinguished between different forms of inertia, which are usually manifested at a variety of levels and throughout numerous agents [34]. 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 a lack of understanding regarding the particularities of big data analytics, and the inertial forces that can possibly slow down implementation and hinder business value from such initiatives [2,17]. Adding to this, there is even less research on how such inertial forces hinder the use of big data analytics toward the development of dynamic capabilities. While many studies argue that big data analytics can strengthen a firm's dynamic capabilities [7,24], very few actually discuss the process of leveraging them toward these capabilities and the inertial forces that emerge at the different stages. In order to understand how these forces emerge and to be able to derive theoretical and practical implications, we begin by surveying the state-of-the-art existing literature on organizational inertia, especially with regard to IT deployment and diffusion.

Notions such as those of organizational inertia, rigidity, path dependence or stickiness have long been in the center of attention for scholars in the managerial science domain [35]. On the antipode of stable and reproducible structures that guarantee reliability and accountability within organizations, inertia represents the downside that hinders desired change and presents obstacles in transformation [36]. One of the main issues 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 [9, 37]. This study is therefore grounded on the extant literature in the domain of IT-enabled organizational transformation and management science that identifies five broad forms of inertia [38–41]. These include *negative psychology inertia*, *socio-cognitive inertia*, *socio-technical inertia*, *economic inertia*, and *political inertia* [9]. In the context of IT research, Besson and Rowe [9] 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"*. According to the authors, identifying the sources of inertia constituted only one level of analysis, with 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.

Building on this distinction between different types of inertia, the first step of our research is to clearly define and understand how these different types of inertia have been examined in the literature and at what level they appear. Negative psychology inertia has been predominantly attributed to group and individual behavior and is based on the 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 play in the face on novel technological deployments, negative psychological reactions can arise, which biases them toward the current situation [42]. Socio-cognitive inertia is mostly focused on malleability due to path dependencies, habitualization, cognitive inertia and high complexity [43]. 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, however, refers to the dependence on socio-technical capabilities, which arise from the interaction of the social systems and technical system and their joint optimization [40]. 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 that make organizations not adopt potentially better alternatives [33]. Finally, political inertia is caused by vested interests and alliances, which may favor that the organization remains committed to a specific type of IT, so that partnerships are not broken [44].

Despite a long tradition in information systems research of examining the forms and effects of inertia, to date in big data analytics literature there has been no systematic study, to the best of our knowledge, examining the types and stages during which such forces appear. From the existing body of research, several research studies have isolated key inhibiting factors during deployment and diffusion [45], while others have elaborated on the different hurdles that may emerge during implementation processes [46,47]. Within these studies there is evidence pointing out to specific types of inertial forces, as, for instance, in the work of Mikalef et al. [48] who mention that in some cases economic inertia caused a problem in the adoption of big data analytics. The authors find 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. Furthermore, they mention that both socio-cognitive and socio-technical issues were present at the group level, where people were reluctant to change their patterns of work and adjust the use of IT to incorporate analytics insight.

Comparable results are reported by Janssen et al. [49], where the authors note that socio-cognitive inertia can be reduced by implementing governance schemes that dictate new forms of communication and knowledge exchange. In another study, Vidgen et al. [12] underscore that inertial forces impact the implementation of big data analytics projects, and that the presence of the right people that can form data analytics teams and implement processes is critical to success. Akin to the previously mentioned studies, Kamioka and Tapanainen [50] find that systematic use of big data analytics was influenced by the attitude of users and top management. These results highlight that there are indeed several different types of inertial forces that come into play, at different levels, and throughout distinct phases of diffusion and routinization. Nevertheless, the identification of inertial forces in the aforementioned studies is not performed in a systematic and exhaustive way, since the main objectives of these studies are to identify critical success factors, therefore broadening the scope of investigation and not focusing on the stages of implementation and the association of big data analytics with strategic processes.

2.2. Diffusion model

A central component of the diffusion process is the existence of a novel technology, especially when it is argued to be a source of organizational performance gains in highly competitive and turbulent industries. Within the existing body of research in the information systems literature, there has been focus on many different types of IT, as well as an exploration of adoption and diffusion at different levels [32]. Within this stream of research, one broad distinction that is commonly made is between a state of adoption, and that of diffusion (continued usage) [51]. From these, studies that focus on the former state, i.e. adoption, typically look at factors that influence decisions to do so, as well as barriers or conditions that prevent organization from beginning to use such technologies [52]. However, literature that looks into the later aspect, i.e. continued usage, most commonly focuses on the individual and not on firm-level dynamics [53]. Therefore, there is an imbalance on the side of research focusing on individuals and organizational aspects with regard to adoption, but largely neglecting the organizational side in terms of diffusion and routinization. From a practical point of view, nonetheless, there exist multiple stages of adoption, diffusion and routinization that are not always easy to separate in distinct phases. Since this study is more focused on the organizational dynamics of the stages of use, rather than explaining adoption decisions or phases of technical implementation, we follow a stage diffusion approach to determine the main sources of inertia in big data analytics projects throughout different phases [29]. The diffusion stages are, as a result, grounded in the general theory of deployment phases as described by Mergel and Bretschneider [29], which has been applied in multiple different contexts [54,55].

According to the theoretical framework proposed by Mergel and Bretschneider [29], the first stage of diffusion is termed *intrapreneurship and experimentation*, where the new technology is typically used informally by individuals within the IT department. Users during this stage typically have little to no knowledge on the new technology and learn through experimentation and trial-and-error, or when the firm decides to invest in some employees with related skills. When at this stage, individual experimenters work to gradually deploy the novel technology throughout the organization and communicate its value with other departments or units. The triggers for this stage of diffusion can be 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 toward its diffusion. This phase may also include the process where different sub-units within an organization adopt different versions of the technology of the technology, and in some cases, even multiple version of the technology. 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. For instance, in organizations that follow a decentralized governance structure, it is likely that more heterogeneous outcomes will be achieved than in centralized organizations with regard to the number and types of technology. The third and final stage is called *institutionalization* in which the new IT solution 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, as, for example, being adopted by partners or collaborators. At 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. One of the downsides though is that there is less experimentation with the new technology and a more routinized use of it, resulting in lower levels of new business opportunities.

In spite of the fact that these stages have been clearly defined in the literature for different types of technological innovations [29], for big data analytics projects and their use in the organizational setting they have not been utilized to date. The prevailing assumption that existing studies build on is that either firms have adopted or haven't big data analytics technologies [56]. This is a critical aspect, as many organizations having possession of the same set of resources, may be on very dissimilar levels of diffusion of that technology [57]. 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 allow us to understand the inertial forces that dominate each one, as well how they can be overcome. Yet, it is critical to associate the stages of big data analytics diffusion and assimilation with how they leveraged in organizations and specifically how they are linked to the value-generating mechanisms. 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. We therefore first introduce the theory of dynamic capabilities and then survey the literature on big data analytics and their relation to business value in order to explain how big data analytics can be used to strengthen the underlying processes that comprise dynamic capabilities.

2.3. Dynamic capabilities

The dynamic capabilities view (DCV) has been one of the most influential theoretical perspectives in the study of strategic management over the past two decades [58]. The theory has also started to gain attention in the domain of information systems due to its high relevance in contemporary business environments, which are characterized by high levels of turbulence and dynamism [59]. In his seminal paper, Teece [18] argues that dynamic capabilities can be disaggregated into three general processes of functions 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 (Table 1) [60]. Teece [18] argues that sensing includes establishing analytical systems of scanning, searching and exploring activities across markets and technologies. *Seizing*, however, entails evaluating existing and emerging capabilities, and investing in relevant designs and technologies that are most likely to achieve marketplace acceptance [61]. Finally, *transforming* includes continuous alignment and realignment of specific tangible and intangible assets [62]. Past empirical research has predominantly examined the outcomes of dynamic capabilities [63,64] with much fewer research studies looking into the antecedents of their formation [65]. From this limited pool of papers, studies have looked at antecedents at different levels of analysis, including the organizational [66], individual [67], and environmental levels [68], to isolate factors that either enable or hinder the formation of dynamic capabilities. Yet, when it comes to the role of information systems as enablers of the underlying dimensions that comprise a firm's dynamic capabilities, there is to the best of our knowledge very scarce work [11,69]. This issue is especially accentuated in the case of big data analytics where there is limited research on how analytics can enhance the underlying dimensions of dynamic capabilities [11], but even more, what factors hinder successful leveraging of these technologies toward the processes of sensing, seizing and transforming.

Despite extensive research 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. Much of the past studies that utilize the dynamic capabilities as a theoretical lens to explain effects of big data analytics assume that such investments are leveraged with negligible resistance toward the strengthening of dynamic capabilities [7]. Furthermore, there is an assumption that simply because big data analytics resources are deployed and firms have invested in them, they are utilized strategically and deliver an optimal effect toward business outcomes. This is an assumption that has been challenged by recent editorials, which call for a more dynamic process of orchestrating and leveraging resources for value realization [6]. The objective of the following sub-section is to discuss how big data analytics have been linked to the value generating mechanisms described in the DCV, before proceeding to explore what inertial forces may hinder such effects in the analysis section.

2.4. Big data analytics as enablers of dynamic capabilities

The potential business value of big data analytics investments in the organizational setting is a topic that is ongoing for almost a decade now [19,70]. Nevertheless, empirical research delving into such claims has only started to appear in the last few years, with the vast majority of research papers being published over the last three years [6,7,14,71]. While some of the studies explicitly define the impact that big data analytics has on the underlying processes that comprise dynamic capabilities, others discuss such effects in a more equivocal manner. For instance, Gupta and George [4] argue that firms that develop a big data analytics capability will be better attuned to market responses, and as such, have a stronger sensing capacity. Similar claims are made by Côrte-Real, Ruivo, and Oliveira [72] who argue that big data analytics can enable organizations to generate business insights into primary activities. Adopting a more holistic perspective, Conboy et al. [11] showcase how big data analytics can be leveraged to enhance sensing, seizing, and transforming processes. The authors illustrate the different ways by which the underlying processes can be strengthened and the requirements in terms of data characteristics when doing so. For instance, moving beyond sensing, the findings from the eight case studies suggest that firms can leverage big data analytics toward seizing opportunities through the activities of real-time process orchestration, dynamic resource allocation, customer risk profiling, and prioritizing target customers.

While not specifically examining the role of big data analytics as an enabler of dynamic capabilities, several other studies have provided important insights into the process of leveraging such technologies toward important organizational outcomes. For instance, Lehrer et al. [5] use the lenses of materiality and affordances as analytical devices to describe how big data analytics afford two fundamentally different types of innovation: automation and human-material practices. Building on a similar theoretical lens, Dremel et al. [14] identify four big data analytics actualization mechanisms which include enhancing, constructing, coordinating, and integrating, which are manifested in three different levels. These mechanisms are argued to be central in realizing value from big data analytics investments within the socio-technical systems they are utilized and leveraged. Other recent empirical work has also included the contingencies of the internal and external environment in the shaping of value from big data analytics investments. For instance, Mikalef and Krogstie [73] identify the different configurations of resources and contingencies that lead to generation of incremental and radical process innovation capabilities. These studies, as well as others, highlight that realizing business value from big data analytics presents some distinct characteristics. *First*, big data analytics require maturation and iterative cycles of learning and adapting. *Second*, there exist different stages of maturity regarding big data analytics diffusion toward

Table 1
Dynamic capabilities and underlying processes.

	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	[18]
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	[18,62]

organizational objectives. *Third*, the big data analytics outcomes are shaped by the internal and external contexts. *Fourth*, in leveraging big data analytics, different levels within an organization (e.g. individual, group) can influence outcomes with ripple effects.

The existing body of research has provided great insights into the potential value that big data analytics can deliver, as well as on the complexities of the leveraging process [14,25,26,71]. Nevertheless, there is a lack of research looking at big data analytics projects as a process of gradual assimilation and routinization. In other words, the literature has largely overlooked the stages that organizations go through when deploying their big data analytics investments toward organizational and, particularly, strategic goals. While big data analytics were relative new notions a few years ago and most organizations were at early stages of adopting these technologies, now they have become increasingly more central in every day operations [74]. Delving into this issue is both timely, as more and more organizations are experimenting with big data analytics following the forerunners, and of high importance, as understanding the hindering forces and creating governance and deployment plans can streamline use and strategic value generation. The aim of this study is therefore to identify the inertial forces that emerge during different stages of big data analytics assimilation and understand how they hinder the emergence of dynamic capabilities.

3. Method

3.1. Design

Since empirical research on the inertial forces that emerge during leveraging of big data analytics toward dynamic capabilities is at an early stage of maturity, we adopted an exploratory multiple case study method [115]. We opted for the multiple case study research method as it allows for the collection of a rich description of phenomena and a detailed explanation of developments that are not well understood in the literature from the perspective of multiple key actors [75]. Furthermore, in our study design we chose to adopt a multi-case study design since it allows a replication logic, through which a set of cases are treated as a series of experiments, each serving to confirm or disconfirm a set of observations [116]. Given that the objective of this study is to explore the inertial forces that emerge during different stages of diffusion, assimilation and routinization of big data analytics for the enhancement of a firm's dynamic capabilities, the multiple case study approach is highly suitable as it enables an interaction with many different instances of those "living the case" [76].

Before initiating the study, the researchers were aware that many of the uses and applications of big data analytics toward the enhancement of dynamic capabilities would be quite subtle, and in some circumstances even hard to detect and verify. Therefore, the exploratory research approach by using multiple case studies can help detect such effects [75]. By doing so, the researchers can isolate the inertial forces for each of the processes of sensing, seizing, and transforming and elucidate specific, subtle, and even complex roles that big data analytics had in enabling these capabilities. The choice of the multiple case study approach is also beneficial where control over the behavior is not required, and where data can be collected through observation in a non-intrusive manner [75]. We conducted our research in firms from different industries, as this allows us to capture a wider spectrum of possible inertial forces, and combinations of those based on the different profiles of firms. 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.

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 [77]. As big data analytics deployments are a relatively new development for many organizations, it was important that we followed an approach that incorporated a broad selection of organizations to capture such phenomena.

3.2. Cases

With regard to the selection of companies that were included in our study, we chose among firms that demonstrated somewhat experience with big data analytics, which meant that those that were still in the pre-adoption phase were automatically excluded (i.e. firms that had not adopted big data analytics but were considered to do so in the near future). Companies that were included in the study based their operations primarily in the Netherlands, Norway and Italy, and appropriate respondents were identified through several steps of contacting people within each organization and presenting the nature and scope of the study. Through this process, we were able to locate those employees who were best suited in answering the questions posed in the interview guideline. To ensure that the sample of companies had been using big data analytics, respondents were screened and were asked several questions regarding their investments. Specifically, we asked them several questions including what their definition of big data and big data analytics was in their firm, what types of investments they had performed in big data analytics over the last year(s) (i.e. what types of data they had acquired, what infrastructure they had purchased, within the time-frame of 1–2 years), in which areas of business they use analytics insight, as well as what was their overall strategy when it came to such investments. From these questions we were able to determine whether a company had indeed engaged with big data analytics or was a very early stage of planning. Those companies that were still at the planning phase, meaning that they had not rolled out any form of big data analytics in their operations, were excluded from our sample. We also used the paper of Mikalef, Pappas et al. [1] to define what was meant with big data analytics, and to ensure that respondents had the same understanding as us on what it entailed.

The remaining companies had either just recently started experimenting with big data analytics or had invested considerable time and effort in gaining value from their investments. Furthermore, we focused mostly on medium- to large-sized companies since the complexity of the projects they were involved in would give us a better understanding of the spectrum of inertial forces that appeared, particularly with regard to cross-unit interactions. Nevertheless, some small and micro firms were also added in our sample since they present unique characteristics (e.g. smaller budgets, more direct communication channels, and less diverse operations) and a different set of conditions compared to medium or large firms. For instance, such companies have been frequently noted as having limited resources due to limited capital, therefore limiting their ability to engage with new and emerging technologies [51]. In addition, micro and small firms represent a very large percentage of firms especially in Europe, so examining the inertial forces that appear in these companies has some important practical implications that can also help guide policy making. Finally, the firms we chose in our sample operated in moderately to highly dynamic markets, which necessitated the adoption of big data analytics as a means to remain competitive [78].

These companies are also subject to mimetic pressures to adopt big data analytics, since in most cases they perceived a threat that competitors would outperform them if they did not follow the big data analytics paradigm. As a result, efforts in developing strong organizational capabilities via means of big data analytics were accelerated. We selected different companies in terms of types of industries 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 and having an international orientation.

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)

3.3. Data collection

Data were collected over a 16-month period from May 2017 to September 2018. The data collection method consisted primarily of personal face-to-face interviews, a method that is well established for collecting beliefs, opinions, and experiences of involved stakeholders, and especially for exploratory research. In particular, such interviews allow for real-time clarification and expansive discussions, which highlight the factors of importance as well as their implications and interdependencies, allowing the researcher to follow up on insights in the course of uncovered mid-interviews and adjust the questions and structure accordingly [79]. Nevertheless, 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, which are subject to their own biases. However, 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. Specifically, we asked respondents to ground their interview responses based on their own experiences according to the guidelines of Schultze and Avital [80].

Primary sources consisted of the direct interviews that were conducted with key respondents in firms, which were recorded and transcribed. The interview procedure focused on their attitudes, beliefs, and opinions regarding their experience with big data analytics initiatives that their firm had undertaken, as well as the challenges they had faced, or where continuing to face with leveraging such investments toward strategic goals. To avoid any bias in responses, data were collected through semi-structured interviews with managers that were directly involved in the big data analytics initiatives. These respondents were selected due to their involvement in big data analytics projects in positions where they had communication and oversight of individuals from different functions, and thus had a more holistic perspective. 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 [75]. To aid analysis of the data after the interviews, all interactions were recorded with each interviewee's consent, and were subsequently transcribed, proof-read and annotated by the researchers. In cases where there existed some ambiguity, clarification was sought from the corresponding interviewee, either via telephone or by e-mail.

Secondary sources of data were used to corroborate statements of the interviewees. These included published information about the firms in the form of annual reports, online corporate information, posts on social media, as well as third-party articles used. Respondents were also asked if they could share presentations that were used over the process of big data analytics assimilation, other internal non-confidential documents, as well as white papers and project reports. Within these data sources, the aim was to identify statements of respondents regarding the applications of big data analytics, the stage of technology deployments, as well as major challenges or obstacles that occurred during assimilation. We then used these data sources and asked respondents if they corresponded to the information that they had provided us through the interviews. This approach allowed us to get some further information from the respondents based on supplementary data that emerged, which contributed to obtaining richer insights on the assimilation of big data analytics in their organization.

Two of the co-authors completed the independent coding of the transcripts in accordance with the defined themes as identified in Table 3. 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 the inter-rater reliability of the two coders was greater than 90 percent [81]. The primary and secondary data, along with the clarifications by contacting respondents, afforded rich access to multiple data sources [82], which are particularly important when examining the process of information systems adoption, and it provided an opportunity to obtain a detailed understanding of the empirical setting [83]. These sources were used to add richness to the analysis of the cases that were selected and analyzed using the open and axial coding techniques [84].

3.4. Data analysis

To empirically analyze the data, an iterative process of reading, coding, and interpreting the transcribed interviews and observation notes of the 27 case studies was followed [87]. This was done using the software package NVivo. At the first stage of our analysis, we identified and isolated the main concepts based on the past literature that was discussed in earlier sections, routing them in the corresponding literature. Specifically, we used the work of Besson and Rowe [9] as a starting point to define the different types of organizational inertia, and thus developed a coding scheme so that we could identify and thematically attribute the responses of the interviewees. Furthermore, to distinguish the stage at which an organization was in terms of big data analytics diffusion, we utilized the stage model of technology diffusion as described by Mergel and Bretschneider [29].

Through the descriptions provided by the authors regarding the characteristics of each distinct stage, we were able to identify for each organization the phase that correspond to their current status of diffusion of big data analytics. Two of the co-authors performed this task individually, and then results were compared and discussed until a consensus was reached. Finally, we used the definitions and conceptualizations of the three processes that comprise dynamic capabilities as described by Teece [18] in his seminal work, to identify toward which type of objective big data analytics were leveraged, and used the micro-foundations framework presented by Conboy et al. [11] to more precisely anchor activities on the underlying processes of big data analytics use. These theoretically grounded concepts were used to code data and generate our results.

For each case the standardization method was used to quantify these characteristics using an open coding scheme [75]. By following this approach, we were able to cluster primary data in a tabular structure, and through an iterative process to identify the relative concepts and notions that were applicable for each case. Collectively, these concepts (Table 3) comprise what is referred to in the literature as organizational inertia [9]. The underlying rationale argues that there are several barriers when examining the process of value generation from big data analytics. These barriers appear during the different diffusion stages and are manifested as various types 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 [88].

Following the transcription of interviews and assigning them thematic tags, as those described in Table 3, we started aggregating finding and identifying common patterns. During the transcription and tagging, we also added labels regarding the stage of diffusion to which they were linked. We used several thematic tags, including those that referred to the inertial forces, the processes of dynamic capabilities toward which big data analytics were targeted, as well as mechanisms used to overcome barriers. More specifically, the inertial forces and how they are presented in big data analytics projects are summarized below grouped based on the underlying processes of dynamic capabilities they were oriented toward strengthening. We used this tabular information to collect information about the organizations, and then based on the focus of the interview and the stage of diffusion and the type of capability that was targeted, proceed to form clusters.

In the cases where the stage of diffusion and the type of capability were similar, but the combinations of inertia types were dissimilar, we created further clusters (e.g. clusters D and E or G and H). This was done by identifying similar combinations of inertial forces which were independently coded by two of the authors. The realized value of a firms' big data analytics is therefore considered to be determined by a multitude of factors that influence outcomes. These findings were then corroborated with the secondary data sources to ensure that they were aligned. The third author then independently assessed the collected data in relation to the cluster the organization belonged to and the inertial forces that emerged. Cases that were ambiguous were further discussed between the co-authors, and additional data were incorporated into the analysis before reaching a consensus. To establish the validity of our results we adopted a triangulation approach that integrated the primary and secondary data, as well as further contacts that we had with respondents to ensure that the outcomes were reliable. Specifically, we followed the approach described by Venkatesh, Brown, and Bala [89] until a 100 percent agreement was achieved between the three co-authors.

In sequence, and after applying the previously mentioned method on the collected data, we visualized the outcomes in the form of a matrix to showcase the presence of an inertial force at a specific stage of diffusion, and in relation to the specific underlying process it is oriented toward [90]. When asking respondents about their experiences and progress with big data analytics, we included questions regarding the stage during which this happened, who were the main involved parties, as well as what organizational capability it had an influence on and the

Table 3
Thematic support for organizational inertia, definitions, and supporting literature.

Type of Inertia	Definition	Level (s)	Supporting Literature
Negative Psychology	Resistance to change due to overwhelming negative emotions caused by threat perception	Individual	[9,34]
Socio-Cognitive	Rigidity due to the re-enactment of norms, collective beliefs and values	Groups, Business Units, Organizations	[9]
Socio-Technical	Inflexibility in change due to the developed pattern of interactions of human actors with information technology	Individual, Groups	[9,40,85]
Economic	Resistance to change due to the resource allocation decisions between exploration and exploitation	Business Units, Organizations	[9,33,86]
Political	Unwillingness to change due to vested interest and alliances	Business Units, Organizations	[9,44]

mechanisms used to alleviate inertial forces. In this way we were able to capture information about the form of inertia, the stage of adoption, diffusion, or routinization that the hindering force appeared, as well as dynamic capability process(es) it was oriented toward enhancing. We discuss the outcomes of our findings in the section that follows.

4. Findings

In Table 4, the presence 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 space indicates the absence of it in any interview. This effectively translates to an understanding that the respondents did not believe that the specific inertial force had an effect during that stage and toward the respective dynamic capability process. Each column represents a cluster of firms that shared similar combinations of inertial forces, belonged to the same stage of diffusion of their big data analytics projects, and were targeting the same underlying process of dynamic capability. The companies that belonged to each cluster are presented in the note below Table 4.

4.1. 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, column B those that are in the order from chaos stage, and column C those that are at a level of institutionalization. Each column corresponds to a cluster of companies that share similar inertial forces. We set a minimum of 3 cases as the threshold for a cluster to form a solution in alignment with analyses of set-theoretic results [91]. The granular level descriptions of inertial forces for the corresponding clusters of sensing processes are summarized in Table 5.

4.1.1. Intrapreneurship and experimentation

Companies in this group were piloting early projects in an attempt to identify areas to which they could react. Among the sample of responses, there was a bit of diversity in terms of the sensing activity big data analytics were geared toward. For example, most companies mentioned that they were piloting projects for customer requirement analysis and segmentation, while others were using big data analytics for predictive maintenance or for sensing possible interruptions of operations in case of weather fluctuations. From the data analyzed, it was apparent that a major barrier was the lack of economic resources, negative psychology from employees in the technical departments, and inflexible work practices that revolve around established ways of sensing external conditions. Respondent from C.5 stated the following:

> *"When we began our experimentation, we were quickly surprised with the associated investments we would need to make to actually get things going [….] It was a hard battle to fight for since it required considerable investment from top management with limited understanding if this would pay off in the end. [….] there was strong negativity from them as they were not sure about how results were obtained and how accurate data were. […] there was great reluctance to change as they were in fear of changing how they typically did things […] and believed that they would lose the power to choose how to do their job".*

The respondent for C.26 added the following specifically on the negative psychology part:

> *"[…] I tried to convince my co-workers that we should adopt big data analytics to identify fault occurrence in our machinery. The guys in the IT group saw this with skepticism, which then turned to hostility. […] The main reason through I encountered this resistance was that they were used to doing this in a specific way […] and were afraid that their skills were not sufficient […]"*

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

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

Note: Clusters represented with letters correspond to the following companies in our sample. **A** (C.5; C.8; C.15; C.17; C.20; C.21; C.26), **B** (C.3; C.9; C.11; C.13), **C** (C.12; C.18; C.27), **D** (C.6; C.14), **E** (C.4; C.7; C.24), **F** (C.1; C.19), **G** (C.10; C.16; C.22), **H**(C.2; C.23 C.25).

4.1.2. Order from chaos

For firms that were 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 toward 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 were siloed in other departments. Socio-cognitive inertia was apparent due to the existing norms and regulations around data governance practices, coupled with feelings of fear of loss of authority. During this stage of diffusion, inertial forces appeared to be more apparent in terms of inter-departmental or cross-functional activities, rather than localized within the IT department. 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 […] 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"*

On the specific issue of inter-functional coordination due to socio-cognitive inertia, respondent C.3 noted the following:

> *"What we quickly saw was that when we tried to scale up our analytics efforts and integrate data from the logistics department, we faced a roadblock. Suddenly it was not certain if we were allowed to use the data they had, and there was no one accountable to say who can use what, and for what".*

4.1.3. Institutionalization

Firms that were highly mature in terms of leveraging big data analytics and belonged to the stage of institutionalization were presented with a different set of inertial forces. During this stage of diffusion, hindering forces moved up to the higher levels of management and were predominantly centered around individuals rather than units or teams. Negative psychology by decision makers with regard to the outcomes of analytics, as well as reliance on routinized ways of making decisions, was found to be the main inhibiting forces with regard to leveraging big data analytics for sensing opportunities and threats. Lack of transparency of how data are collected, cleansed, analyzed, and visualized is noted as being a significant inhibitor of leveraging big data analytics fully toward managerial decision-making and taking action based on insights. Specifically, the respondents from C.27 stated the following:

Table 5
Granular level descriptions of inertial forces for sensing processes.

	Sensing		
	A	B	C
Inertia			
Economic	Organizational	Organizational	
Political			
Socio-cognitive		Business units (Inter-functional communication)	
Negative psychology	Individual (IT employees)		Individual (Decision makers)
Socio-technical	Individual (IT employees)		Individual (Decision makers)
Stage of diffusion	Intrapreneurship and experimentation	Order from chaos	Institutionalization

"[…] 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".

Adding to the previous, the respondent from C.18 claimed the following:

"[…] We need to show how insight is produced since there is a lot of discussion among the managers about if they should trust what is being told to them, […] I believe this is partly because of the lack of trust in the data, and also a fear that they are being told what to do rather than consulted. […]".

4.2. 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. With relation to the diffusion stages of companies, we found cases for firms that belonged to two of the three stages of diffusion and with varying underlying inertial forces that were inhibiting successful leveraging of big data analytics. The granular level descriptions of inertial forces for seizing processes are presented in Table 6. The clusters D, E and F correspond to those depicted in Table 4.

4.2.1. Order from chaos

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, the respondent 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. […]"

The respondent from the oil and gas firm (C.7) also noted that a combination of negative psychology and socio-technical inertia affected the use of big data analytics for seizing opportunities, as described in cluster E. Specifically, the respondent noted:

"[…] When we introduced our findings and described to them how our analytics was more accurate in predicting failures and prioritizing maintenance plans, they were unwilling to use the solution we have developed due to familiarity with the old process. […]"

4.2.2. Institutionalization

Apart from the two clusters of companies that belonged to the diffusion stage of order from chaos (D and E), there was one cluster that corresponded to firms that were in the institutionalization phase (F). Firms that belonged to the F cluster had embedded 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. This was predominantly based on the fact that they believed that data were not complete or sufficient to generate useful insight on which they could ground their decisions. For instance, the respondent from company C.1 stated the following:

"[…] 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"

4.3. Transforming

The final process of dynamic capability is that of transforming, which is essential if firms want to capitalize on the generated insight that helps sense and, on the actions, required that underpin seizing. To ensure that business analytics delivers a sustained business value, it is therefore 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

Table 6
Granular level descriptions of inertial forces for seizing processes.

	Seizing		
	D	E	F
Inertia			
Economic			
Political			
Socio-cognitive	Business Unit		
Negative psychology		Individual (Line function managers)	Individual (Department managers)
Socio-technical	Business Unit	Business Unit	
Stage of diffusion	Order from chaos	Order from chaos	Institutionalization

Table 7
Granular level descriptions of inertial forces for transforming processes.

	Transforming	
	G	H
Inertia		
Economic		
Political		
Socio-cognitive		Group (Functional unit)
Negative psychology	Individual (Top-level managers)	
Socio-technical	Group (Management group)	Group (Functional unit)
Stage of diffusion	Institutionalization	Institutionalization

decision-making [64]. The summaries of the granular descriptions of inertial forces for transformation processes are depicted in Table 7.

4.3.1. Institutionalization

In activities of transforming we only found firms that were in the stages of institutionalization, with two different clusters appearing in results. In cluster G, negative psychology emerged as a hindering factor since these firms were in the process of transforming their business models based on big data analytics. This aspect was also coupled with a presence of strong socio-technical inertia. For example, C.22 were piloting a new business model, which developed personalized advertisements based on the use of their existing mobile-phone application. The personalized advertisement platform was then launched as a standalone application; however there was doubt from top management about the success that it could have since the firm was venturing into unknown territories. The company initiated several test launches and even retracted the application due to fear that it may provide users with irrelevant content. This was also based on the fact that positive results were expected much sooner that were actually needed for them to become apparent. 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"*

While the two solutions were quite similar in outcomes, 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, and a resistance to move toward a fully computerized solution. This was primarily based on the thought that customers would notice the lack of human interaction and develop negative perceptions, as well as due to the fact they enjoyed the way of interacting with customers. The belief was that they could better interact with customers and that they could also learn more from them than a computer-based system. Specifically, the respondent noted that:

> *"[…] 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"*

4.4. Cross-case analysis

After analyzing the data in each case, we used cross-case analysis to uncover patterns and to see if the findings were applicable across the cases [92]. Specifically, we analyzed the cases similarities and differences in terms of the levels and types of inertial forces throughout the different stages of diffusion, as well as with regard to the underlying process of dynamic capabilities that they were targeting to enhance. The differences were discussed, and we focused on the reasons that these variations occurred. In sequence, we compared the patterns for consistency and aggregation, refined the clusters of cases, and contrasted them which helped in developing our framework to summarize our key findings. By constructing the framework based on the cross-case analysis, we are also able to develop deeper insights into the use of big data analytics for the enhancement of dynamic capabilities, and to propose directions for future research and ways in which this study opens up new perspectives for the discourse of big data analytics and business value research.

4.4.1. Within-clusters analysis

We started by examining the cases that belonged to the same clusters (i.e. A, B, etc.), as depicted in Table 4. The cross-case analysis within these companies showed that there was very little variability in the stage of diffusion within those companies, and that the forms of inertia were almost identical. This finding was interesting to observe, as many of the companies in each of the clusters belonged to different industries. For example, in cluster A, although companies C5 and C8 belonged to very different industries they both faced the same combination of inertial forces when it came to developing their sensing capabilities. Specifically, inertial forces from top management in relation to investing economic resources, coupled with negative psychology and socio-technical resistances from the technical departments, were consistently presented in organizations that were in the intrapreneurship and experimentation phase. In addition, these companies were piloting their big data analytics projects around sensing activities, as they were perceived to be the easiest to accomplish. An interesting observation on this was that the lack of data resources and communication with other departments in changing organizational routines inhibited companies in the first phase from being able to enable seizing and transforming capabilities by means of big data analytics. As such, the inertial forces not only hindered the realization of big data analytics–driven sensing, but also obstructed the attainment of seizing and transforming activities.

In organizations that managed to move to a more mature diffusion stage of big data analytics (i.e. *"order from chaos"*), a different set of inertial factors hindered the realization of value. For example, within the group of organizations that formed cluster E, negative psychology and socio-technical resistance came from different groups. Although these companies belonged to the same phase of diffusion (i.e. order from chaos), the presence of resistance unfolded in different departments. This had to do primarily with the routinization of big data analytics in core business activities, and the diversity of organizations within this cluster meant that different business functions were then introduced to the deployment of solutions. For example, is case C7, big data analytics were being deployed to streamline predictive maintenance operations and dynamically orchestrate relevant personnel. This meant that the sub-sea operations department and the HR units were being introduced to the use of big data analytics insights to adapt operations. Negative psychology and socio-technical inertia were therefore presented from those specific departments, which are contrasted with case C4 that concerned the media industry. In case C4, where big data analytics were being deployed to provide personalized service offerings to customers, the business units that were being affected were the marketing and design departments. While a common set of factors hindered the value generation of big data analytics, these examples show that there is variability in terms of the involved departments.

With regard to companies that had reached an *"institutionalization"* stage of big data analytics use, there were a consistent set of factors that inhibited value generation from seizing and transforming activities. Specifically, these had to do with changing value streams and incorporating a new logic of business models into the existing organization. The main underlying challenge that many top-level executives faced was how to incorporate a different way of calculating value that was generated from big data analytics, which did not directly translate to profitability. In addition, transition plans for gradually phasing out conventional ways of conducting activities and introducing big data analytics were necessary to overcome resistance to change. Finally, when it comes to big data analytics that were used by top-level executives, there needed to be reassurance that throughout the lifecycle of information all data and activities of processing and developing insight were grounded on established approaches that did not introduce bias that could potentially skew results. This poses a requirement on organizations to formalize and clearly document the processes and methods used from data collection to analysis and insight generation.

4.4.2. Between-clusters analysis

The between-cluster analysis attempted to uncover common and distinct aspects of the patterns of inertial forces that emerge during big data analytics use. The outcomes of this analysis were very interesting as they uncovered two important aspects that contribute to our framework, a) how inertial forces shift depending on the maturity of big data analytics diffusion, and b) what unique aspects emerge when targeting the underlying processes of dynamic capabilities. The first aspect is very important as it provides a roadmap for organizations to overcome the inertial forces that hinder value generation and proceed to more mature phases of diffusion. By doing so they are also able to generate more business values and pursue a broader set of options. This leads to the second aspect, which has to do with the potential to pursue more diverse strategies using big data analytics. As organizations overcome inertial forces, they are able to move from a restricted set of activities, such as sensing emerging opportunities and threats, to seizing and transforming operations. The more the use of big data analytics was routinized and diffused from an activity mostly taking place in the IT department to the one that takes place throughout the entire organization, the greater the set of options of applications and use in key organizational activities.

Our findings therefore document that clusters of firms that developed mechanisms to overcome their inertial forces were able to pursue a broader set of activities in relation to dynamic capabilities. In addition, as organizations overcame these barriers, they were also able to strengthen their respective processes. For example, companies in clusters A and C differed significantly in terms of the sophistication of methods and techniques used for sensing, as well as the breadth and detail of sensing by using big data analytics. More specifically, organizations in cluster A conducted sensing mostly though the IT department and relied on data that was available at the time within organizational boundaries. Furthermore, sensing activities were more focused on a narrow set of activities. In contrast, organizations that belonged to cluster C had adopted more sophisticated techniques for analyzing data and generating insight, with sensing spanning several activities from different departments. Companies belonging to cluster C had also developed more approaches to integrating data from external sources. For example, company C.27 was integrating weather forecasts from the meteorological agency of the country they operated in combination with data from their network devices, such as bandwidth usage and device temperature to proactively sense where faults were likely to occur in their infrastructure. This company was also integrating data about housing projects to identify where they would need to expand their network and to estimate what type of usage new users would require from their physical infrastructure to proactively sense demand.

The findings regarding the inertial forces and the levels in which they are present also highlight some key points as to how they can be overcome. For example, organizations moving from an *"intrapreneurship and experimentation"* stage to an *"order from chaos"* one typically require top management support, a clear strategy that places data-driven decision-making as a short-term goal, financial resources to invest in appropriate technologies, data and skills, data governance schemes, and a restructuring of the collaboration and communication patterns between departments. When it comes to moving from the *"order from chaos"* phase to the *"institutionalization"* stage another set of important enablers were present that dampened the inhibiting effects of inertial forces. These included training of middle and unit managers on techniques and methods of big data analytics, setting up accountability and responsibility measures for departments in terms of outcomes and uses of big data analytics, arranging regular inter-functional meetings with heads of units to discuss the use and outcomes of big data analytics in operations, and establishing relevant key performance indicators (KPIs) around activities where big data analytics were used. The results of this analysis combined with that of the within-cluster analysis enabled us to proceed to design a framework of big data analytics diffusion.

4.5. A framework for big data analytics–driven transformation

This section presents a framework of big data analytics-transformation that is grounded in our analysis of inertial forces. Our framework explains the main inertial forces as they appear as well as key actions taken to overcome these. We distinguish these based on the stage in which they appear as well as on the organizational level at which they are presented. Specifically, our framework which is depicted in Fig. 1 highlights some of the main inertial forces as they appear at different stages of big data analytics diffusion and highlights some core mechanisms for overcoming them as indicated by the respondents. These mechanisms can be taken as best practices as organizations progress with their big data analytics investments and gradually embed insights into an increasing number of business activities. In relation to past studies, this framework differs as it provides a perspective around big data analytics, which is focused on the gradual diffusion and the inhibiting forces that emerge during this process. Much of what has been reported in the past literature sees adoption of big data analytics as a largely static event that occurs during one point in time. In reality though, diffusion of such technologies is an ongoing process, and as it unfolds within the organizational fabric there are different inertial forces coming into play, which hinder value generation.

As such, this work is one of the first that highlights the inertial forces as they appear at different stages of diffusion. Past research has placed more emphasis on the resources that need to be invested and the value generating mechanisms [6,7], but does not say much about how organizations should approach such investments and the obstacles they will face during diffusion. In a recent editorial by Mikalef, Pappas et al. [17] the importance of examining the process which organizations go through to integrate big data analytics into their operations was highlighted as particularly important. By distinguishing between three phases of diffusion, our framework documents the mechanisms that are noted as being critical for realizing increased business values. These findings also highlight the obstacles that organizations face when attempting to reconfigure their operations by means of big data analytics. Drawing on the inertial forces that appear at different stages, it is also possible to identify the potential business value to the firm and where it is limited. For example, organizations that are not able to pivot out of the intrapreneurship and experimentation stage and diffuse and align their big data analytics projects according to strategic goals will not be able to achieve certain types of performance outcomes. In the framework presented in Fig. 1, we visualize these as dotted lines, which form the boundaries of business value. Specifically, we refer to the three types of business value as *localized exploration*, *operational optimization*, and *strategic transformation* accordingly.

While past research has noted that maturing big data analytics capabilities can result in varying levels of business value, here there is an attempt to date to isolate the inertial forces in each stage and draw a distinction in terms of the realized organizational value. Most empirical studies assume that organizational performance indicators will have a variation of effect depending on the level of big data analytics diffusion. Nevertheless, our framework and findings indicate that big data analytics projects also differ in terms of scope. Therefore, the type of business value that can be expected differs significantly. For instance, our empirical evidence showed that organizations that were in an *"intrapreneurship and experimentation"* phase focused on sensing activities, which were predominantly performed in a localized manner. These projects involved a smaller number of business units relying mostly on existing internal data from singular departments. However, organizations that were able to move to the *"order from chaos"* phase were able to pursue a broader set of options including seizing, and transforming activities, which enabled them to attain operational optimization through big data analytics. The possibility however to develop radically new products, services, or applications based on big data analytics was only possible once they had overcome the barriers of the *"institutionalization"* phase.

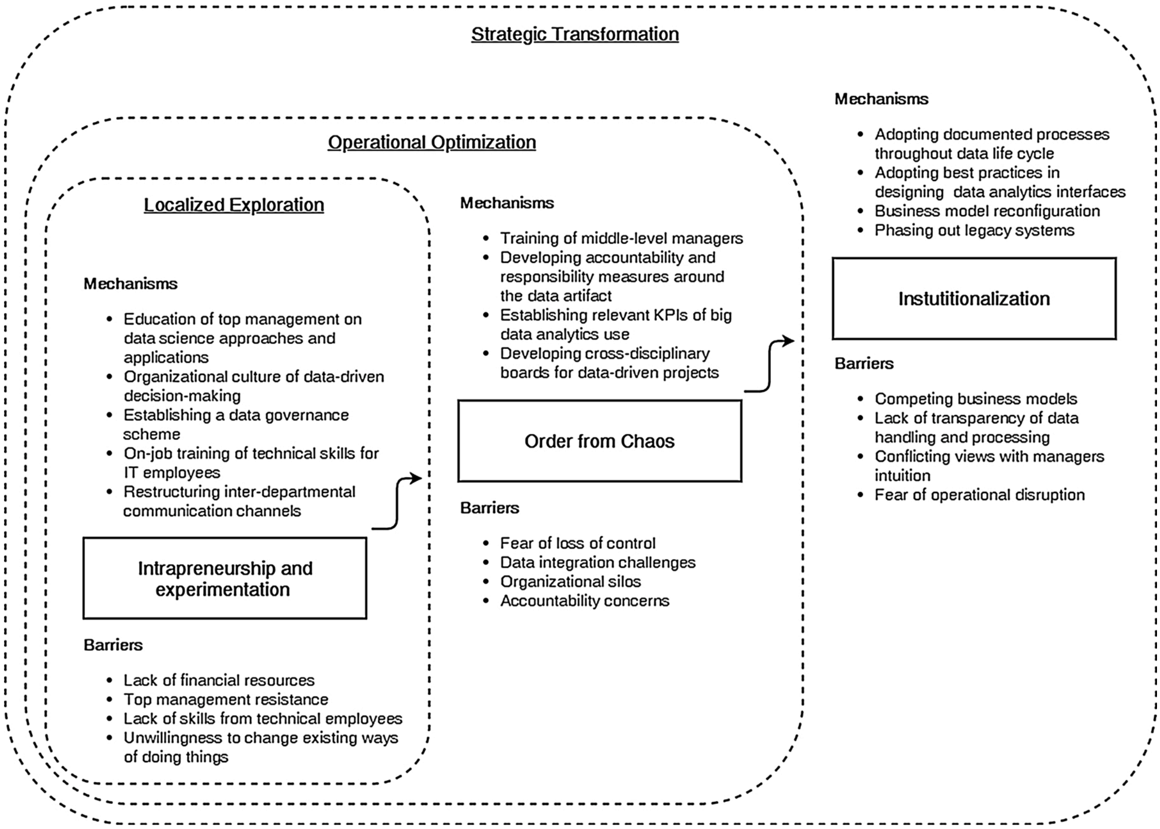

Fig. 1. A framework for big data analytics–driven transformation.

Apart from the practical relevance that the framework may have for managers and other practitioners, there are also some important research implications that can be explored, particularly in relation to what has been done in prior research. First, the findings indicate that it may be more relevant to categorize the samples of organizations depending on their level of big data analytics diffusion when attempting to capture business value. This is mostly because strategic-level outcomes may not be accurate reflections of big data analytics use patterns in the organization if they are still at an early phase of diffusion. Second, the choice of level of analysis and the corresponding theories to examine such effects can differ based on the phase of big data analytics diffusion. So, for example, macro-level effects may only be relevant for organizations that are in the *"institutionalization phase"*, and the corresponding approaches to capture such effects need to take into account the unit of analysis to which they are relevant. Third, prior research has largely overlooked the process of diffusing big data analytics, but mostly focused on the outcomes that can be identified. What our framework demonstrates is that big data analytics needs to be materialized into capabilities that are of relevance and importance to organizations, and the process of doing so requires overcoming rigidities and barriers. As such, a static approach when considering big data analytics resources may not provide an accurate reflection of the actual ability of organizations to leverage such resources [17]. Hence, understanding the process and the evolution of big data analytics capabilities can tell us more about why some organizations fail to realize performance gains, and how to overcome common inertial forces during this process.

5. Discussion

The objective of the present study is to examine how inertial forces manifest in big data analytics projects, and specifically how such forces emerge during different stages of diffusion. We examined these in relation to the specific underlying process of dynamic capabilities that they are oriented toward. To do so, we grounded our study on prior literature, which differentiates between five different types of inertia; *economic*, *political*, *socio-cognitive*, *negative psychology*, and *socio-technical* [9]. Specifically, we examined how these forces of inertia are manifested in contemporary organizations through 27 case studies and at different stages of diffusion. We distinguished the different stages of diffusion based on the diffusion model of Mergel and Bretschneider [29] that identifies three stages of assimilation of new technologies in the organizational fabric. Our results indicate that value from big data analytics 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 analytics investments or anticipating inertial forces that will occur at later stages.

5.1. Research implications

The outcomes of this study provide several important implications for research. First, the study demonstrates that even if firms make the necessary investments in big data analytics resources, this by itself is not sufficient to generate business value, as there are multiple ways through which such value can be obstructed. Much of the recent empirical research on big data analytics has focused on three main streams: 1) the core resources required to leverage big data analytics [1,4], 2) the potential value that such investments can offer [3,6,7,22,93], and 3) the mechanisms and approaches for leveraging such investments in the socio-technical context [5,14,94]. Yet, to date we have a limited understanding regarding the forces of resistance that emerge as organizations deploy big data analytics, and how these differ depending on the different stages of diffusion. Capturing the impediments that organizations may face, especially in relation to the attainment of strategic business value, has been argued to be an important research question that requires further exploration according to recent editorials [16].

This study has therefore sought to identify what types of inertial forces may hinder value generation and the effectiveness of leveraging processes when it comes to big data analytics deployments. By isolating different patterns of hindering forces that materialize throughout various stages of diffusion of big data analytics, we are able to offer a fresh perspective, which takes into account the rigidity that organizations develop as a result of routines [95]. One of the underlying assumptions, that is often overlooked by the existing body of research on big data analytics, is that organizations are often sticky when it comes to organizational transformation [96]. This stickiness results in different forces of resistance when introducing new digital technologies, such as big data analytics, as they inevitably incur changes at many different levels within the organization (C. [97]). One of the findings from past studies in digitally driven organizational transformation is that inertial forces also emerge at different stages of maturity, or diffusion of new technologies [9]. Nevertheless, much of the body of research on big data analytics has not empirically examined how these different stages of diffusion prompt varying forms of inertia [25].

Raising the issue of inertia during different stages of diffusion goes counter to existing studies that assume that simply because firms invest in relevant big data analytics resources, they will be able to achieve performance gains and enhance their dynamic capabilities [7]. This study essentially posits that there are several aspects that must be considered before assuming that just because big data analytics resources have been acquired, they will automatically confer value. Much of the existing empirical research conceptualizes the notion of a big data analytics capability as the sum of all resources [1,4]. This view obscures that fact that to be able to develop a firm-wide capability, organizations must be capable of overcoming the different forces of inertia that appear at different stages of diffusion. Our results indicate that throughout the three stages of *intrapreneurship and experimentation*, *coordinated chaos*, and *institutionalization,* and depending on the type of strategic outcome that is targeted, there are different combinations of inertial forces that hinder the attainment of objectives.

Some recent work has begun to explore the socio-technical dynamics that contribute to the leveragability of big data analytics toward key organizational outcomes [5,14]. These studies examine the affordances that big data analytics enable in the organizational setting [5], as well as the mechanisms for mobilizing and orchestrating such digital innovations [14]. Nevertheless, although they outline mechanisms of leveraging big data analytics, they do not highlight the inertial forces that appear, and specifically how these differ depending on the underlying processes that are targeted toward strategic business value [16, 17]. This study therefore provides a complementary perspective that bridges the literature of business value of big data analytics, with that of digital transformations and dynamic capabilities [69,98]. By expanding the perspective of big data analytics literature and introducing the notions of inertia and staged assimilation, we highlight the importance of thinking of diffusion of novel technologies such as big data analytics, as a gradual process, which sparks forces of resistance at different stages and levels. As a result, it contributes to the understanding, from a theoretical standpoint, of how to mobilize and leverage big data analytics investments for strategic purposes in the organizational context [99].

By challenging the claim that big data analytics resources lead to value creation – through dynamic capability enhancement, this study highlights the issue of governance of such projects. While there is a stream of research into the issues of information governance [100,101], 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 [102]. In addition, how firms should handle individual-, group- and industry-level dynamics is a topic that is hardly touched upon. While management literature has started to talk about the resource orchestration mechanisms and schemes that are necessary to leverage resources into capabilities [103], the same cannot be said about IS studies, with little work been done relating to big data analytics [14]. Our findings highlight the areas that need to be considered during the different diffusion stages, as well as the hindrances they create. Developing mechanisms, therefore, to counteract these barriers is an area with high research relevance.

Furthermore, this research adds to the growing stream of IS studies that employ the dynamic capabilities theory ([59,104]). While management studies talk about the hindering aspect of path dependencies which create rigidity in strategic transformations, IS studies largely disregard such effects that digital transformations may have toward strategic outcomes [98]. Introducing any novel IS artifact is likely to generate inertial forces; nevertheless, this link has yet to be examined within the context of the dynamic capabilities' theory. IS studies frequently adapt management theories to explain the value-generating mechanisms of IS investments, such as the Resource-Based View (RBV) and Absorptive Capacity [105–107]. In doing so, researchers have critically looked into the theoretical underpinnings of these frameworks and unearthed the underlying assumptions. This has yet to be done though with the DCV, leading to a widespread assumption that internally within the firm resources are leveraged optimally and unobstructed by any hindering forces. By demonstrating the link between inertial forces toward the processes that comprise dynamic capabilities, we empirically showcase that there are indeed several different types of inertial forces that emerge at different stages of diffusion of big data analytics. These forces are also present at different levels within the organization (e.g. individual, group, team). Therefore, it is important to understand that when forces hinder the emergence of dynamic capabilities, these can transcend individuals and diffuse into group or even business units' levels before becoming organizational-wide issues. Thus, it is critical to understand these technology-driven inertial forces and manage them, so that business value is not hindered.

Finally, a last implication for research concerns the chosen perspective of this study to differentiate firms based on their big data analytics diffusion levels. Past studies assume that resource investments can be a good proxy to understand how much use of big data analytics takes place within organizations [21,73,108]. This creates the false assumption that simply because resources have been invested in, they are actually used and leveraged toward business goals. Our results clearly indicate that organizations fall into different clusters with regard to their diffusion levels, and that these also have an impact on what types of dynamic capability processes are actually leveraged. While those that are in an early stage of diffusion focus on simply sensing emerging opportunities and threats, those that have institutionalized their big data analytics implementations utilize them for transforming their business models and core operations. This illustrates that the level of big data analytics diffusion strengthens different types of processes, which are also likely to create a different set of strategic business value. This is something that has not been empirically explored in prior big data analytics studies, as it is generally assumed that big data analytics will deliver value equal to the investments that have been made [4,7].

5.2. Managerial implications

Adopting a practical perspective, the results of this study highlight some potential strategies that can be adopted to mitigate the effects of the different types of inertia. The results from our empirical study indicate that inertia can be present at many phases of diffusion, so action needs to be taken throughout projects. Hence, 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 insights generated by big data analytics. 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. A way to address this is to adopt methods for prioritizing business cases and developing analytics to support those that are of the greatest importance. Hindle et al. [109] propose such a method, which ensures that the various stakeholders that are involved have an aligned understanding of the top business priorities and the analytics methods used to support decision-making. Similar approaches have been proposed by researchers and practitioners, and start with developing a shared view of the business objectives that need to be attained and then gradually developing plans about how big data analytics can be used to support these [110].

While adopting big data analytics methodologies is a good way to ensure that stakeholders have a shared understanding of the priority areas big data analytics should be targeted to address, it is equally important to establish appropriate governance schemes. Tallon [101] highlights the importance of developing practices throughout the organization, which indicates how data should be managed during its economic lifecycle. By fostering such policies and procedures, organizations remove the barriers and existing silos of data ownership, and as a result reduce potential conflicts that may exist. Doing so also provides organizations with a common way of handling the data resource, thus reducing socio-technical, and socio-cognitive inertia that may occur due to unclear roles or procedures. In other words, establishing a clear and concise information governance scheme sets well-defined roles, procedures, and relational practices, which employees at different positions can adhere to. Several such approaches have been proposed depending on the scope of the big data analytics projects and the context in which they are deployed which practitioners could use as references when developing their governance practices [111,112].

When it comes down to the IT department, educational seminars and incremental projects seem to be the way to limit negative psychology barriers. This allows employees to be educated in the necessary skills that are needed for the big data analytics transition, rather than being left alone to navigate how to do so [50,88]. Several such online educational tools have been developed and have proven to be successful in training employees and providing them with a step-by-step approach to develop their big data analytics competencies [113,114]. By doing so, negative psychology inertia can be dampened as employees will feel more comfortable with the transition and the required skillset to do so. Also, providing a clear sense of direction as to what kind of analytics are to be performed on what data are of paramount importance. It is commonly observed that many companies delve into the hype of big data analytics without having a clear vision of what they want to achieve. By clearly defining the three main stages of diffusion, 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. As illustrated by our results, during the first stages of diffusion, there are certain departments and individuals that need to be prioritized compared to those that emerge at a later stage. This enables managers to develop strategies that have concentrated efforts in managing the appearance of inertial forces as projects gradually mature and assimilate within the organization.

5.3. Limitations

Although this research is a first attempt to uncover forces of inertia and the levels at which they present themselves, it does not come without certain limitations. First, we looked at companies that have adopted big data analytics, a more complete approach would be to look at what conditions cause other firms to not opt for big data analytics. It may be the case that many organizations do not even start to engage with big data analytics due to a completely different set of aspects. Second, while we briefly touched on the issue of middle-level managers not following insight generated from big data analytics, 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. While many believe that the value of big data analytics is in generating insight that can be put into action, the true potential is only if the insight is actually followed. If it is not this begs the question as to why managers decide to utilize it and how this can be fixed. This is a future that should be examined since the value of big data analytics cannot be clearly documented in the absence of knowledge about strategic or operational choices. Finally, although we adopted a multiple case study approach to identify the broadest set of inertial forces possible, it may be that there are different clusters of configurations that hinder leveraging big data analytics effectively that we have not captured. Therefore, a next necessary step would be to expand the sample and conduct a quantitative study, which would provide a greater confidence in the clusters of companies and the resistances they face.

CRediT authorship contribution statement

Patrick Mikalef: Conceptualizaton, Data curation, Formal analysis, Investigation, Writing - original draft, Writing - review & editing. **Rogier van de Wetering:** Data curation, Writing - original draft. **John Krogstie:** Writing - original draft, Supervision.

Appendix A. Interview Questions

Background

- Can you please tell us a little bit about yourself, your position and your organization?
- How many years have you been working in this position, and how many in your current organization?
- Can you tell us a little bit about the industry in which you operate? Do you have many competitors? Do customer requirements change often?
- Can you give us your definition of big data, and that of big data analytics?
- What are your responsibilities (especially related to BDA)?
- When did your organization start using BDA?
- When did you get involved?
- Why did your organization choose to adopt BDA?
- How mature would you say you are in terms of diffusing BDA within your organization? Why?
- Can you tell us about the data your organization use for BDA? (What data, internal/external, what types of tools etc)?
- Can you tell us about the technical solutions you use? (Hadoop, SQL, Oracle, other…)?

General

- What types of challenges have you experienced when deploying big data analytics?
- Could you say a little bit about your experience and the attitudes of those that were involved?
- Where there are any major setbacks?
- How were these challenges handled?
- What were some major milestones during the leveraging of BDA?
- What major investments have you made in BDA over the past 1–2 years?

Organization

- Can you describe what challenges you encountered for specific applications of BDA?
- Can you tell us about who is involved in BDA? What departments?
- How is the communication between the involved departments?
- Do managers understand the value of BDA?

- Are results of BDA implemented into the business strategy?
- Are there any difficulties in generating insight?
- Are there any difficulties in diffusing this information?
- How is your organization able to find, evaluate and use new knowledge that BDA can provide insight into?
- What are some of the main difficulties you face in determining the areas that big data projects will be focused on?

Performance

- Do you use big data analytics to scan the environment and competitors? If yes in which way and what challenges have you faced in doing so?
- Have you applied big data analytics to improve coordination within your company or with other business partners? By what means and what obstacles did you encounter?
- Have you managed to gain any important corporate insight through big data analytics? Has the company gained new insight concerning its customers, products, marketing strategy etc? If yes, how did you manage that?
- Has big data analytics helped you integrate new knowledge that you were previously unaware of?
- In which way has big data analytics helped you seize emerging opportunities? What challenges did you face when attempting this?
- Through big data do you manage to reconfigure your existing mode of operation? If yes, please elaborate on how and what challenges you faced.
- Would you say that big data and analytics has helped you gain a lead over your competitors? Has it helped in other areas (e.g. slicing costs, reducing personnel, increasing operational efficiency, delivering innovative products/services)?
- Would you say that the investments and efforts put in big data analytics have paid off yet or would they need more time to become visible?
- Are there other positive or negative experience?
- Any thoughts you want to share with us?

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