Big data and business analytics: A research agenda for realizing business value

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Big data and business analytics: A research agenda for realizing business value

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Introduction

As organizations strive to achieve a competitive edge over their rivals, big data and business analytics are now playing an increasingly important role in realizing performance gains (H. Chen, Chiang, & Storey, 2012a). This has signaled an increased interest in the domain by both researchers and practitioners especially over the past few years, with data being now regarded as one of the most valuable organizational resources. Recent studies have begun to empirically demonstrate the value that big data and business analytics have on organizational-level outcomes, such as agility (Ashrafi, Ravasan, Trkman, & Afshari, 2019), innovation (Lehrer, Wieneke, vom Brocke, Jung, & Seidel, 2018), and competitive performance (Côrte-Real, Ruivo, & Oliveira, 2019; Mikalef, Krogstie, Pappas, & Pavlou, 2019). Nevertheless, a recurring finding of these studies is that in order to derive value from big data, firms must develop the organizational capacity to identify areas within their business that can benefit from data-driven insight, strategically plan and execute data analytics projects, and bundle the resource mix necessary to turn data into actionable insight (Gupta & George, 2016; Vidgen, Shaw, & Grant, 2017). While there is significant variation with regards to the term used to denote this capacity, there is overall consensus about the key resources needed to develop a big data analytics or business analytics capability (Gupta & George, 2016).

Past editorials and special issues in IS and management journals have approached the topic of big data analytics from different perspectives. For instance, Sharma, Mithas, and Kankanhalli (2014) suggest several research avenues based on the implications that the use of business analytics creates for decision-making and its, indirect effect on performance. Abbasi, Sarker, and Chiang (2016) map big data and business analytics onto the information value chain and highlight the novel aspects that these technologies introduce from a behavioral science, design science and economics perspective. Chiang, Grover, Liang, and Zhang (2018) emphasize in their editorial on the need to understand how big data analytics in translates to a competitive advantage. The guest editors argue that it is not sufficient to focus on the resources that are needed to extract meaning out of data, but it is necessary to adopt a viewpoint of leveraging data to outperform competition. Pappas, Mikalef, Giannakos, Krogstie, and Lekakos (2018) attempt to explain how the different actors within an ecosystem generate data, and what are the core resources necessary to leverage this data towards digital transformation and sustainable societies. G. Hindle, Kunc, Mortensen, Oztekin, and Vidgen (2019) in their editorial develop a framework where they place business analytics in the organizational and environmental context. Finally, in their editorial of the Academy of Management Journal, George, Haas, and Pentland (2014) expand on different facets of big data analytics, from the sources of data generation, aspects pertinent to data sharing, privacy and ethics, ways of analyzing big data, and concluding with implications for management research.

All of the abovementioned editorials, and special issue introductions present different important perspectives of big data with regard to IS research. In this editorial, our goal is to synthesize the existing body of knowledge and uncover some core assumptions that warrant further research in the context of big data and business analytics business value. We therefore expand on these themes and present a framework that illustrates the associations between the key elements of big data and business analytics and highlight some potential areas for meaningful research questions. For each of these research questions we propose a set of directions and expand on their importance for both research and practice. As big data and business analytics are becoming an increasingly core component of contemporary organizations, it is important to examine how such technologies and their implementations can be directed towards meaningful outcomes that generate business value. The gradual routinization of big data and business analytics into organizational operations presents many challenges, and a plethora of opportunities for novel research than spans different domains and research traditions.

The editorial is structured as follows. In the next section we overview the existing research on big data and business analytics and identify the major research streams within this domain and the results they have produced. This is done to put into perspective the current body of research and the current surge of studies on the business value of big data and business analytics and to then critically assess the studies that have been performed under each stream and uncover underlying assumptions and unexplored research areas. Based on the critical assessment, we present a framework and discuss some potentially interesting research opportunities, followed by a discussion of how the papers included in this special contribute towards these directions.

Big Data and Business Analytics: What have we learned and where do we go now?

The interest in big data and business analytics has grown exponentially over the past decade, even since the first seminal articles discussing the potential of big data to revolutionize the way we work, live and conduct business (Brown, Chui, & Manyika, 2011; H. Chen et al., 2012a; LaValle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011; Manyika et al., 2011; McAfee, Brynjolfsson, & Davenport, 2012). Ever since then, IS researchers have attempted to explore the phenomenon of big data and business analytics and understand how organizations can create and capture value from their data resources. A reflection of this explosion in research interest is represented in the graph below depicting the number of articles that have been published and appear in the academic database Scopus. To capture these articles, we used a query for all the years from 2010 when big data and business analytics started to emerge until 2018 which is the last full year for which all publications have appeared online, consisting of the keywords "big data analytics" or "business analytics". In total, 5.495 articles were retrieved. The growth of articles is illustrated in Figure 1. This figure shows that the field is still expanding, and that a growing number of researchers are concentrating their efforts into the domains of big data and business analytics. The increasing number of research articles produced in these domains provides a strong motivation to synthesize some of the major research streams within this area and to explore what underlying assumptions warrant challenging. Critically assessing the overall field and the questions researchers ask also helps identify major streams that have not received the necessary attention, despite strong practical need. We proceed in the following sub-sections to overview some of the topics that have received the most attention in the field and synthesize the knowledge accumulated to date.

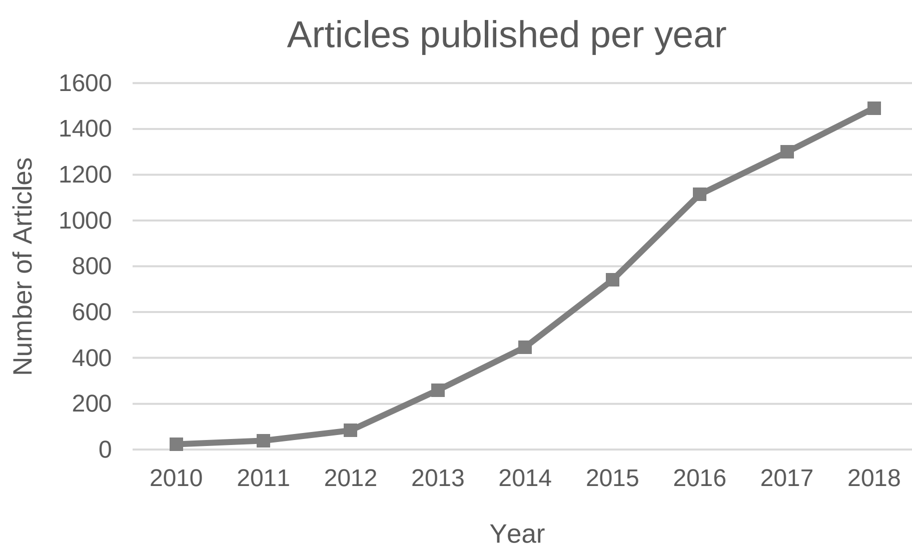

Figure 1 Articles published per year for the time period 2010-2018

While big data and business analytics broke into the spotlight in both management and IS literatures approximately a decade ago, they are not new ideas and have been presented under different labels throughout the discourse of research. Nevertheless, while these ideas and concepts have re-appeared several times throughout the history of IS and management studies, since 2010 they have managed to dominate the interest of academics and practitioners. This can be attributed to a multitude of factors that jointly contributed to the emergence of the big data and business analytics phenomenon. First, the storage costs and capacity has been on a constant drop, allowing for vast volumes of data to be captured at a low cost (Ji, Li, Qiu, Awada, & Li, 2012). Second, the processing power capable by modern day computers has increased significantly, coupled with a concurrent drop in the price of provisioning it (Sagiroglu & Sinanc, 2013). Third, the emergence of sensors and connected devices in an increasing number of physical and digital artifacts has enabled organizations to capture data that was previously hard to monitor in real-time (Atzori, Iera, & Morabito, 2010). Fourth, the maturity of network infrastructures and the growing business models on cloud computing (e.g. platforms-as-a-service) have made it possible for a large proportion of organizations to access scalable services and transfer their data and generate insight in almost real-time with a minimal cost (Agrawal, Das, & El Abbadi, 2011). The combination of the above-mentioned factors has made it possible to operationalize advanced analytics techniques which require vast amounts of data, and to generate insight that is both meaningful and accurate in a cost-effective manner.

These coinciding conditions have re-ignited the interest of practitioners and academics regarding the way organizations can develop their big data and business analytics initiatives and realize performance gains from their efforts. As big data and business analytics projects, typically, involve several departments, and entail organizational transformations at many different levels, they create an interesting environment with several unexplored areas. Research has made great strides, especially over the last five years in examining the big data and business analytics phenomenon, particularly when taking into account the large degree of adoption across organizations and the manifold activities it can be geared towards. Furthermore, recent years have seen the deployment of big data and business analytics in many different industries and also spanning private and public organizations (H. Chen, Chiang, & Storey, 2012b). These dissimilar contexts also create a unique set of opportunities, but also a distinct set of challenges for the successful use of big data and business analytics. A growing body of empirical research has started to tackle these problems and approach the field of big data and business analytics from many different perspectives. For each of these perspectives we provide a brief synthesis and discuss potential areas where more attention needs to be paid. While a lot of the earlier work in the area has assumed that the introduction of big data and business analytics would not necessitate substantial changes to incorporate these new technologies into the organizational fabric, recent studies have begun to challenge this assumption and examine adoption projects from an broader perspective (Vidgen et al., 2017). Drawing on earlier research, we contend that big data and business analytics will require organizations to radically redesign how such initiatives are approached, designed and refined, how resource planning and orchestration is executed and strategically aligned, as well as re-valuate their expected performance outcomes, their association with strategic objectives and, as a result, develop appropriate KPIs. In figure 2 depicted below we develop a research framework which largely covers the researched agenda we develop in the following text.

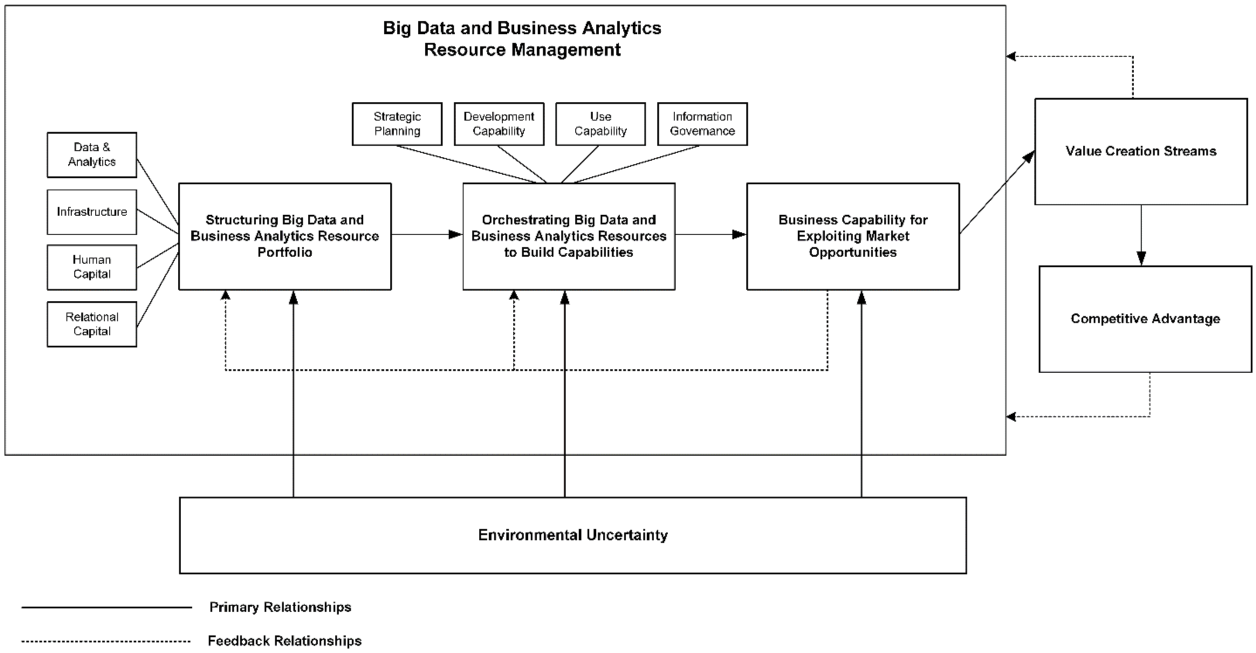

Figure 2 A research framework for big data and business analytics resource management

Based on the foregoing discussion and on the above illustrated framework, we propose three research questions on which we base our research agenda:

- How do big data and analytics methods coalesce to provide actionable insight?
- How do resource bundling and orchestration practices influence organizations big data and business analytics leveraging capacity?
- What organizational capabilities can big data analytics enable or automate, and what is the effect of doing so?

Data attributes, sources and analytics methods

Perhaps the defining aspect that gave rise to the notion of big data are the attributes that characterize the term, namely through the four Vs, volume, variety, velocity, and veracity (Akter & Wamba, 2016; Mikalef, Pappas, Krogstie, & Giannakos, 2018). While several papers have discussed additional dimensions relevant to the domain of big data as defining attributes (Seddon & Currie, 2017), only recently have empirical studies started to examine the implications that these may have on leveragability of data towards business outcomes and the implications they create for the IT and business side. For instance, the paper of Günther, Mehrizi, Huysman, and Feldberg (2017) discusses the implications of adopting an inductive vs a deductive approach when it comes to big data analytics. Their analysis of studies revealed that in most studies a deductive approach is followed that starts from collecting data without a pre-defined purpose and then seeking to generate theoretical explanations based on exploration and analysis (Constantiou & Kallinikos, 2015). Here, the variety and granularity, along with the velocity and volume of data may create challenges to understand what insight can be extracted ex-ante from the data sources (Kim, 2015), and incur excessive costs for companies owing to the costly nature of doing so (Tallon, Ramirez, & Short, 2013). Adopting a deductive approach to big data and business analytics projects may mitigate such issues, but on the other hand may lead to the emergence of situation where confirmation bias is present (Herschel & Miori, 2017). In such cases, analytics insight may be developed based on selective data to confirm preexisting viewpoints, while disregarding data that refutes it. The same point is also made by Lycett (2013), who argues that pre-existing frames of reference carried by analysts and managers may have an important influence on the data elements that are selected, how they are analyzed, and what interpretations can be produced by them. These frames of reference usually are embedded in the cognitions of analysts and managers and operate in a sub-conscious manner. An article by Zoldan (2013) argues that big data and business analytics projects require skepticism and caution to avoid statistical false positives and incorrect findings that may lead to bad decisions. The above discussion therefore suggests that there is a need to understand the strengths and weaknesses of each approach, as well as how major shortcomings of each can be overcome in order to produce objective and valuable insight. Specifically, we suggest that researchers delve into the following research question:

- What benefits can different approaches towards big data and business analytics yield, and how can their associated shortcomings be overcome?

When looking into the defining characteristics of big data, a stream of research has looked into the issues and implications that these create for organizations, and specifically for the types of decisions they are used to inform. For instance, Conboy, Mikalef, Dennehy, and Krogstie (2019) examine through eight case studies the importance of Vs for supporting analytics-based activities used towards sensing, seizing, and reconfiguring processes. The implications that these characteristics have for each of the underlying processes of dynamic capabilities is discussed, as well as the challenges that they create from the transition from one activity (e.g. sensing) to another (e.g. seizing). Other studies have looked into complementary aspects of the data that is utilized for analytics projects, as for instance Côrte-Real et al. (2019) who examine the data quality attributes of completeness, accuracy and currency in generating organizational capabilities and ultimately leading to performance gains. Their results indicate that data quality components are significant contributors of overall competitive performance. Similar results are also noted by Janssen, van der Voort, and Wahyudi (2017) who indicate that big data will provide little value if it is not accurate and people are not able to interpret the decisions. While these studies highlight some of the attributes of data that influence use and leveragability, there are still many unique characteristics relating to big data and its lifecycle which are still not explored, particularly in relation to value creation (Surbakti, Wang, Indulska, & Sadiq, 2019). For instance, the interdependencies or restrictions that data create for analysis and interpretation are seldom talked about and even more sparsely empirically researched. In addition, the data resource is frequently seen as a static artifact that is the starting point of analysis and insight generation, while in reality data-driven projects often include several iterations where data artifacts are added, removed or refined, and appropriately granular and suiting data resources are used to inform analysis and generate insight. This is an area that has not been addressed in much depth in, particularly through deductive research approaches (G. A. Hindle & Vidgen, 2018). This draws attention to the following research question:

- How do attributes of the data influence their use and leveragability, and what are the implications of these data attributes throughout their lifecycle of use?

With regards to the analytics methods applied to data in order to transform data into actionable knowledge, there are a large number of studies that assume that bundling resources will in turn influence the sophistication of the analytics methods used to extract such insight (Wamba et al., 2017). A large number of published studies emphasize on the capability of organizations to utilize big data analytics, with empirical findings suggesting that a more mature resource base will result in enhanced levels of competitiveness (Côrte-Real et al., 2019; Mikalef, Krogstie, et al., 2019). Such capabilities are typically underpinned by a technological infrastructure to handle the storing and processing of the data, and the human skills and knowledge to actually transform data into valuable insight (Gupta & George, 2016). Dremel, Herterich, Wulf, and Vom Brocke (2018) illustrate through a case study in a large automotive manufacturing company that different analytics approaches, and hence socio-technical configurations, can lead to different forms of value. The authors shed light into the actualization of four big data analytics affordances which address establishing customer-centric marketing, provisioning vehicle-data-driven services, data-driven vehicle developing, and optimized production processes. Although popular press has drawn a distinction between the different types of analytics sophistication and the potential performance advantage that they can produce (e.g. predictive, prescriptive, and descriptive analytics), such levels of analytics are seldom factored in when considering the potential competitive performance gains that can be achieved or the types of capabilities they are oriented towards strengthening. This discussion raises the following question:

- How does the use of different analytics techniques influence the performance potential that organizations can achieve through big data and business analytics?

Big data and business intelligence capabilities, orchestration, and data governance

Recent studies in the area of big data and business analytics acknowledge that firms must develop a firm-wide capability of leveraging their big data and business analytics resources in order to realize value (Gupta & George, 2016). This perspective has gained traction within the academic and practitioner communities as it sees big data and business analytics as organizational-wide investments that necessitate resource investments at different levels throughout the organization (Wamba et al., 2017). While there is a slight divergence about what resources are important in generating value from big data and business analytics, there is a consensus that firms must adopt a perspective that goes beyond the technical side when considering effects and deployment of big data and business analytics (Mikalef et al., 2018). Nevertheless, while there is a strong focus on the resources that lead to a firm-wide capability, there is considerably less focus on how this ability matures from initial experimentation with a new technology to routinization, as well as what the obstacles are during this process. In other words, there has been significantly less research on how organizations develop their big data and business analytics capabilities over time, and what are the constraining or inhibiting factors during this process. Furthermore, there is very little empirical attention on what are the driving forces or pressures that motivate organizations to initiative big data and business analytics projects. While there has been some empirical work on the driving forces of adoption, such as that of Dubey, Gunasekaran, Childe, Blome, and Papadopoulos (2019), we still know very little about how the contrasting pressures, enablers and constraints interact to initiate adoption and gradual maturation of big data and business analytics. This highlights two important research questions for future research:

- How do organizations develop their big data and business analytics capabilities?
- What are the constraining forces, pressures and enablers while adopting and maturing big data and business analytics?

In conceptualizing a firm's ability to leverage big data and business analytics, a large proportion of papers have based their empirical examination on the theoretical underpinning of the Resource-Based View (RBV) of the firm (Gupta & George, 2016; Mikalef, Boura, Lekakos, & Krogstie, 2019). According to this theoretical lens, firms that are in position of certain resources will be more likely to achieve competitive performance gains due to the ability to orchestrate these resources towards specific goals. Nevertheless, an underlying assumption that these resources are actually orchestrated and mobilized in an effective manner that can lead to desired outcomes. This assumption has largely been ignored by big data and business analytics research, with most studies adopting the logic that just because some key resources are in place, they are orchestrated and leveraged efficiently. This aspect of how resources are arranged and instrumented has been a part of a long discussion in management literature (Sirmon, Hitt, & Ireland, 2007) and partially adopted in IS studies (Wang, Liang, Zhong, Xue, & Xiao, 2012). Nevertheless, within studies that focus on big data and business analytics, aspects such as to what extent are such technologies integrated in strategy thinking, how can continuous alignment with strategic objectives be achieved, and what are optimal ways of sourcing, procuring, or developing analytics solutions are often overlooked. As these technologies start to become increasingly more used in organizational settings, there will be a growing need to understand the optimal ways of mobilizing the relevant resources towards strategic and operational objectives. This leads us to the following research question:

- What are the structures, processes and activities necessary to bundle big data and business analytics resources into organizational capabilities?

An important component of developing the above-mentioned organizational capability is being able to access, utilize, and transform the raw data input into valuable insight. Doing so necessitates that the structures, procedures and roles have been established to enable the necessary flow of data towards the individuals or entities that require it, while taking into account aspects of security, privacy and ethics when doing so. In this direction a stream of research has emphasized o the importance in the age of big data and business analytics to talk about the role of information governance (Tallon et al., 2013). A growing discussion has centered on the fact that while IT governance has been in the center of focus, there has been considerably less attention on the information artifact and how it should be managed. Anecdotal claims as well as exploratory research has revealed that unclear organizational ownership roles over the data resource, unspecified processes of how to manage and transform data, as well as organizational structures that restrict efficient flow of data and information are some of the main contributors to big data and business analytics project failures (Popovič, Hackney, Tassabehji, & Castelli, 2018; Tallon, 2013). While some studies have explored the main dimensions and components of information governance (Tallon et al., 2013), there is still very little empirical evidence to explore its effects and mechanisms of use in the organizational setting. This raises the following research question:

- What are the effects of different forms of information governance practices in creating value from big data and business analytics investments?

Business value of big data and business analytics, mechanisms and moderators

One of the main narratives around big data and business analytics is that they can lead to more informed insight, that in turn can result in better decisions and hence, greater performance gains (Sharma et al., 2014). Despite this assertion, a large proportion of empirical studies assume a direct relationship between big data and business analytics capabilities and performance outcomes, or through mediating organizational capabilities (Wamba et al., 2017). Nevertheless, the human component in this association is seldom taken into account, even though it is up to humans to interpret outcomes and make decisions. This point is also noted by Sharma et al. (2014) that note that humans are often subject to several forces that can potentially inhibit or sway their judgements and decision-making processes, such as using heuristics or basing decisions on personal biases or predispositions. Recent work in the domains of strategic management has attempted to pin down the psychological foundations of organizational capabilities (Hodgkinson & Healey, 2011), and uncover areas where decision-makers rely more on intuition and instinct rather that data-generated insight. There is an extensive debate about the limitations and strengths of each approach, nevertheless studies that examine the use of big data and business analytics in the organizational setting, assume that what is produced as insight is truthful and is accurate followed by decision-makers. This of course obscures the fact that in many cases managers tend to overlook the outcomes of analytics or tend to prefer their own judgement to base their decisions on. This highlights two important research questions:

- What are the strengths and limitations of big data and business analytics-based decision-making?
- What factors contribute towards minimizing human biases or use of heuristics instead of insight produced by big data and business analytics?

In terms of directing big data and business analytics outcomes, there has been a growing body of research examining the organizational capabilities which such investments are leveraged towards. A substantial proportion of this research has argued that big data and business analytics can enable the dynamic capabilities of firms, by allowing them to enhance their abilities to sensing emerging opportunities and threats, seize them before competitors, and transform the way the conduct business to accommodate the changing landscape (Mikalef, Boura, et al., 2019; Wamba et al., 2017). Yet, despite such claims analytics applications within organizations span a number of different activities, and for a large proportion of organizations only operate to provide incremental improvements to operations or predict potential faults occurrences and disruptions. In these cases, competitive performance measures are unlikely to be good indicators to gauge the success of such projects. On the antipode, advanced analytics techniques are being deployed to augment human creativity. An example of this is the use of artificial intelligence (AI) by designers, such as the software produced by American based company Autodesk, to enhance and propose designs based on physical constrains. Such use of advanced analytics creates a different set of performance measures on which success of investments can be determined, such as creativity and innovation. Alternatively, objective measures could be a better proxy to capture effects of big data and business analytics (Müller, Fay, & vom Brocke, 2018). The foregoing discussion leads to two important research questions:

- What are the different mediating organizational capabilities though which big data analytics can lead to value?
- What is the relationship between different applications of analytics and the types of performance outcomes that can be achieved?

Adding to the above discussion, it is important to consider the context in which big data and business analytics are leveraged and the contingencies relevant to the environment. A number of studies have started exploring effect that environmental dynamism has, and if the use of big data and business analytics is enhanced under such conditions (Côrte-Real et al., 2019). The argument is that as the speed of change increases, so does the value of big data and business analytics grow as it can produce insight on large amount of data much faster than conventional methods and much more accurately than human cognition can (D. Q. Chen, Preston, & Swink, 2015). In addition, temporal aspects relating to big data and business analytics projects (Conboy, Dennehy, & O'Connor, 2018), as well as the triggers under which they could prove more beneficial are aspects that are of central importance. The paper of Conboy et al. (2018) touches on the temporal complexities of big data and business analytics and raises several factors as part of a research agenda. This debate suggests an important question for future research:

- What are the conditioning factors that can either amplify or dampen the value of big data analytics investments?

Papers in the Special Issue and closing thoughts

The special issue attracted in total 53 papers of which 8 were accepted for publication. These papers approached the domain of big data and business analytics from different angles, providing richness in the field of investigation and generating several interesting implications for research and practice.

Conboy et al. (2018) in their article focus on the concept of time in big data and business analytics as a core element. The authors argue that analytics must cater to temporal complexities of organizations and people using it. They draw on temporality theory and develop a set of temporal factors through which they examine the value of analytics. In sequence their paper develops a research agenda that identifies opportunities to examine time, temporal personalities and other factors when using analytics in the organizational setting.

Pröllochs and Feuerriegel (2018) develop a framework based on automated text mining, so as to identify the key issues faced by organizations. They then quantify the use of language found in materials from firms in order to reveal a firms strengths and weaknesses, highlighting the business unit, activities, and processes subject to risk, comparing findings with competitors in the market.

Dong and Yang (2018) take on the challenge of exploring through systems theory how the use of social media analytics the marker performance and impact of big data analytics. In their study they explain how and why social media analytics creates super-additive value through the synergies in functional complementarity between social media diversity for gathering big data from diverse social media channels and big data analytics for analyzing the gathered big data.

Demoulin and Coussement (2018) focuses on the use of big data and business analytics for text-mining purposes and investigates the factors that contribute to acceptance and use of such technologies in the organizational setting. The findings point out that information quality influences behavioral intentions and text mining usage, through perceptions of external control, perceived ease of use and perceive usefulness. The outcomes of this study also pinpoint towards the important role of top management support in the usage of text mining tools.

Côrte-Real et al. (2019) draw on a strategic management perspective and explore the value that big data analytics and Internet of Things (IoT) capabilities can create based on a sample of 628 European and American firms. Their results suggest that a key antecedent to competitive performance is establishing a good quality of data through relevant dimensions, which can unlock the potential that these technologies offer.

Surbakti et al. (2019) conduct a systematic literature review which identifies 41 factors that relate to the effective use and deployment of big data and business analytics in the organizational setting. The authors cluster these into seven themes. To validate the existence of these factors, they explore 45 published case studies and document their insights into how specific companies use big data to achieve their business objectives. Based on this analysis they propose a framework for future research.

Dremel et al. (2018) build on a revelatory case study and identify four big data analytics actualization mechanisms, which manifest in actions on three socio-technical system levels, i.e. the structure, actor, and technology levels. The examine the actualization of four big data analytics affordances in an automotive manufacturing company and explain how organizational actions contribute to actualizing big data analytics affordances. Based on these findings they provide practical implications that guide practitioners in adoption.

Chung and Zeng (2018) examine the process by which emotion produces influence in online social media networks. In their work, the authors developed a novel framework, a theory-based model, and a proof-of-concept system for dissecting emotion and user influence in social media networks.

These studies touch on several of the previously mentioned research questions and open up further avenues for future research. It is the guest editors firm belief that the emergence of advanced analytics methods that augment and even replace human decision-making will further accelerate the research focus in the domain and expand the inter-disciplinarily of the field. Our hope is that this editorial will serve as an inspiration for future research ventures.

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