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COMPLEMENTARITIES BETWEEN INFORMATION GOVERNANCE AND BIG DATA ANALYTICS CAPABILITIES ON INNOVATION

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Research paper

Abstract

Big data has seen an explosion in interest from private and public organizations over the last few years. Researchers and practitioners have delved into examining the shifts that these technologies entail and their overall business value. In this study we draw on the resource-based view and on recent literature on big data analytics, and address the interplay between BDACs and information governance in shaping innovative capabilities. We theoretically develop the idea that BDAC's help enhance innovative capabilities, and that information governance strengthens this relationship. To test our proposed research model, we used survey data from 175 chief information officers and IT managers. By employing partial least squares structural equation modelling (PLS-SEM), results confirm our assumptions regarding the positive effect that BDACs have on both incremental and radical innovative capability. We also show that the value of BDAC's on radical innovative capability is amplified in the presence of strong information governance, which also has a direct impact of BDAC's. Finally, implications for research and practice are discussed.

Keywords: Big Data, Information Governance, Innovative Capability

1 Introduction

A constantly growing number of firms are accelerating the deployment of their big data analytics initiatives with the aim of developing critical insight that can ultimately provide them with the key to outperform their competitors (Constantiou & Kallinikos, 2015). Following the explosion of data volume, velocity, and variety, substantial developments have been made in the area of techniques and technologies for data storage, analysis, and visualization. Yet, to date, there is very little research on how organizations need to change to embrace these technological development, a limited understanding on the business shifts they entail, as well as limited empirical research on the business value such deployments offer (McAfee, Brynjolfsson, & Davenport, 2012). Relative to the hype that surrounds the notion ofbig data, the empirical work of examining if, and under what conditions big data investments produce business value, remains under-represented, severely hampering business and strategic potential (McAfee et al., 2012). To date, most research has centred on infrastructure, intelligence, and analytics tools, while other related resources such as human skills and knowledge have been largely disregarded (Gupta & George, 2016). Furthermore, the orchestration of these resources, as well as the governance mechanisms that they require continues to be an under-developed area of research (Wamba et al., 2017). Exponential data growth has placed information governance as a critical issue for senior IT and business management when considering the firm-wide big data projects and their value (Mikalef, Pappas, Krogstie, & Giannakos, 2017).

In the past few years, a number of research commentaries have focused on the importance of examining the whole spectrum of aspects that surround big data analytics (Constantiou & Kallinikos, 2015; Markus, 2015). In past literature reviews on the broader IS domain a recurring finding is that a broad variety of aspects should be considered when determining the business potential of IT investments (Schryen, 2013). In addition, the mechanisms through which each technological innovation produces business value needs to be thoroughly examined. Literature in the area of IT business value has predominantly used the notion of IT capabilities to refer to the broader context of technology within firms, and the overall proficiency in leveraging and mobilizing the different resources and capabilities (Bharadwaj, 2000). We therefore deem it necessary to identify and explore the domain specific aspects that are relevant to big data analytics within the business context and examine the ways in which they add value (Mikalef, Pappas, et al., 2017).

While there is a growing stream of literature on the business potential of big data analytics, there is still limited empirical work which significantly hinders research concerning the value of big data analytics, and leaves practitioners in unchartered territories when faced with implementing such investments in their firms. To derive any meaningful theoretical and practical implications, as well as to identify important areas of future research, it is critical to understand how the core artefacts pertinent to big data analytics are shaped and how they lead to business value (Constantiou & Kallinikos, 2015). To address these critical gaps in the literature, we ground our study on two complementary aspects, big data analytics capability and information governance. Building on these concepts, we seek to answer two closely related research questions: (1) Does a firms' big data analytics capability result in an enhanced firm-wide innovative capability, and (2) what is the role of information governance in shaping a firm's big data analytic capability and conditioning its output?

To answer these questions, we build theoretically on the resource based view of the firm which is presented in the next section. In addition, we define the notions of a big data analytics capability and information governance and illustrate how they are conceptually developed. Next, we provide an argument on how big data analytics capabilities have an impact on a firm's innovative capabilities, and how information governance promotes this effect. To answer these questions, we develop a survey-based study and in the Methods section describe the data collection procedures and measures for concept. Finally, we present the results of our empirical analysis, followed by a discussion on the theoretical and practical implication of findings, as well as some core limitations.

2 Conceptual Development

Building and sustaining a competitive advantage is at the cornerstone of strategic management literature, which draws on a number of interweaved elements and notions (Amit & Schoemaker, 1993). The resource based view (RBV) has been generally acknowledged as one of the most prominent and powerful theories in explaining how firms achieve and sustain a competitive advantage as a result of the resources they own and manage (Barney, 2001). Although resources represent the raw materials in the quest of attaining competitive gains, they are insufficient without the underlying ability to utilize and mobilize them in order to harness their potential. In subsequent literature, the notion of resource was subsequently further split to encompass the processes of resource-picking and capability-building, two distinct facets central to the RBV (Amit & Schoemaker, 1993). According to the definitions of Amit and Schoemaker (1993) resources are regarded as tradable and non-specific firm assets, while capabilities as non-tradable firm-specific abilities to integrate, deploy, and utilize other resources within the firm. In this sense, resources represent the input of the production process while a capability is the capacity to deploy these resources with the aim of improving productivity. Resources were further distinguished by Grant (1991) into tangible (financial and physical resources), human skills (employees' knowledge and skills), or intangible (learning propensity and organizational culture). This classification of resources has also been the most widely applied in the IS literature when referring to an IT capability (Bharadwaj, 2000; Chae, Koh, & Prybutok, 2014; Ravichandran & Lertwongsatien, 2005) (Bharadwaj, 2000; Ravichandran & Lertwongsatien, 2005; Chae et al., 2014). In this respect, the RBV has been the principal theoretical backbone for examining how IT resources can be utlized in order to form IT capabilities, which in turn can conditionally influence competitive performance (Melville et al., 2004 (Melville, Kraemer, & Gurbaxani, 2004; Zhang, 2005). This view has gained research interest in recent years, since numerous studies have empirically demonstrated that firms that possess superior bundles of IT resources tend to outperform their competitors (Kim, Shin, Kim, & Lee, 2011). Similarly, in the context of big data analytics the same categorization of resources can be followed which are discussed below (Mikalef, Pappas, et al., 2017).

But while in some studies there may be an assumption that the existence of resources leads to the development of capabilities, others emphasize on the importance of governance, as the mechanism of orchestrating resources into valuable business-enhancing capabilities. The organizing level is concerned with how these resources are mobilized and utilized through structures, processes, and roles to deliver business value. The expression of particular resources towards a strategic objective depends on the people applying their knowledge, integrating their knowledge, interacting and coordinating actions; this is possible through the establishment of role, structures, and processes, or else governance. Abstracted to the domain of IS, IT governance has been subject to much discussion, and is associated with the implementation of the IT strategy towards business objectives (Sambamurthy & Zmud, 1999). With the increasing embeddedness of big data in firm strategy, the role of information governance has gained a renewed interest, particularly in relation to orchestrating resources into strong big data analytics capabilities and translating insight into action (LaValle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011). Yet, there is limited understanding on the role that information governance has on forming a firm's big data analytics capability, and on how it can impact strategic outcomes.

2.1 Big Data Analytics Capability

Despite the limited, but rapidly growing in number, published research on big data, there are some studies that have emphasized on the challenges that companies face during the implementation of big data projects (Gupta & George, 2016; Mikalef, Framnes, Danielsen, Krogstie, & Olsen, 2017; Vidgen, Shaw, & Grant, 2017). Specifically, within the information systems (IS) domain, researchers recognize that the success of big data projects is not only a result of the data and the analytical tools and processes, but encompasses a broader range of elements that need to be considered (Garmaki, Boughzala, & Wamba, 2016). To address this issue, and following the established literature on IT capabilities (Bharadwaj, 2000), the notion of big data analytics capability (BDAC) has been put forth (Gupta & George, 2016; Wamba et al., 2017). A big data analytics capability is broadly defined as the ability of a firm to capture and analyze data towards the generation of insights by effectively orchestrating and deploying its data, technology, and talent (Akter, Wamba, Gunasekaran, Dubey, & Childe, 2016; Kiron, Prentice, & Ferguson, 2014). While several definitions have been proposed so far, some focus on the necessary processes that must be put in place to leverage big data (Cao & Duan, 2014; Olszak, 2014), while others emphasize on the investment of necessary resources and their alignment with strategy (Xu & Kim, 2014). In essence, the notion of BDA capability extends the view of big data to include all related organizational resources that are important in leveraging big data to their full strategic potential.

Following the classification framework of Grant (1991), big data-related tangible resources include, data, technology, and basic resources (Gupta & George, 2016). In the context of developing a big data analytics capability, perhaps the core resource is the data itself. As previously mentioned, the defining characteristics of big data is its volume, variety, and velocity (C. P. Chen & Zhang, 2014). However, it is frequently mentioned that IT strategists and data analysts are particularly concerned with the quality and availability of the data they analyse (Brinkhues, Maçada, & Casalinho, 2014). While data itself is a core resource, it is also important for firms to possess an infrastructure capable of storing, sharing, and analyzing data. Big data call for novel technologies that are able to handle large amounts of diverse, and fast-moving data (Gupta & George, 2016). One of the main characteristics of such data is that it is in an unstructured format and requires sophisticated infrastructure investments in order to derive meaningful and valuable information (Ji-fan Ren, Fosso Wamba, Akter, Dubey, & Childe, 2017). As such, basic resources such as financial support is necessary, especially since investments may not start yielding any substantial results immediately (Gupta & George, 2016). With regards to human skills, literature recognizes that both technical and managerial-oriented skills are required in order to derive value from big data investments (Wamba et al., 2017). In a highly influential article, Davenport and Patil (2012) address the important role that the emerging job of the data scientist will have in the context of big data. While one of the most critical aspects of data science is the ability of data-analytic thinking, such competences are not only important for the data scientist, but throughout the organization; particularly, for employees in managerial positions (Prescott, 2014). Finally, concerning intangible resources, a data-driven culture and organizational learning are noted as being critical aspects of effective deployment of big data initiatives (Mikalef, Pappas, et al., 2017). In firms engaging in big data projects, a data-driven culture has been noted as being a key factor in determining their overall success and continuation (LaValle et al., 2011). Nevertheless, due to the constantly evolving technological landscape associated with such technologies, it is important that a logic of continuous learning is infused in organizations that invest in big data (Vidgen et al., 2017).

While empirical studies on the business value of developing a big data analytics capability are rather scarce, some early research has demonstrated a positive overall association. Gupta and George (2016) find that a big data analytics capability has a beneficial effect on a firms' market and operational performance. Wamba et al. (2017) demonstrate that a big data analytics capability has positive returns on firm performance directly, and indirectly, through a mediated effect on process-oriented dynamic capabilities. While these are just some of the early studies that suggest a positive impact of big data analytics capabilities on performance, more research is needed to understand the mechanisms through which data-based insight is transformed into action. Thus, it is important to examine the mechanisms through which a firms' big data analytics capability can impact performance, and specifically try to understand how organizational capabilities are influenced.

2.2 Information Governance

The issue of IT governance has been at the spotlight for both researchers and practitioners of over two decades. Prior empirical studies demonstrate that firms that manage to establish a robust IT governance scheme, are more capable of orchestrating their IT resources, developing a strong IT capability, and ultimately, outperform their competitions (De Haes, Van Grembergen, & Debreceny, 2013; van Grembergen, 2007; Xue, Liang, & Boulton, 2008). With the explosion of interest in big data, the interest has not shifted to a subset of IT governance, information governance. Information governance is defined as defined as a collection of competences or practices for the creation, capture, valuation, storage, usage, control, access, archival, and deletion of information and related resources over its life cycle (Mikalef, Pappas, et al., 2017; Tallon, Ramirez, & Short, 2013). As there are multiple facets related to the governance of IT, Weber, Otto, and Österle (2009) suggest that information governance encompasses activities relating to decision-maker roles (structural practices), decision tasks (procedural practices), and person responsibilities and development (relational practices) (Tallon, 2013). Structural practices are responsible for determining key IT and non-IT decision makers and their corresponding roles and responsibilities when it comes to data ownership, value analysis, and cost management. Structural practices include, for instance, explicit declarations about the main roles of setting policies and standards for protecting and using data. They also can encompass the establishment of technical committees to oversee compliance with internal policies or with legal rules about data retention and resource management (Rasouli, Trienekens, Kusters, & Grefen, 2016). Operational practices are revolved around the processes and ways by which organizations execute information governance. These practices span a series of activities including data migration, data retention, cost allocation, data analytic procedures, and access rights. These organizational practices can differ based on the type of data analysed, or the type of insight that is explored. Finally, relational practices are concerned with the formalized links between employees of the technical and business sides. They encapsulate practices and means of knowledge sharing, education and training, and strategic planning (Kooper, Maes, & Lindgreen, 2011).

3 Research Model

The main premise that this research builds on is that information governance is directly associated with the formation of a strong big data analytics capability (BDAC). Establishing structural, procedural, and relational practices around big data is argued to drive the development of a firm's big data analytics capability. The main responsibility of information governance is to answer the question, *"what information do we need, and how do we make use of it and who is responsible for it?"*(Kooper et al., 2011). Information governance can be viewed as a framework to maximize the derived value from information within the firm, which requires a series of actions to effectively orchestrate and leverage related resources, and transform them into a big data analytics capability. Structural practices are important in doing so since they are concerned with the systematic arrangement of people, departments, and other subsystems within the organization (Peppard & Ward, 2004). The structure of big data analytics teams within organizations and the respective flow of data and information is a critical aspect. Early studies note that defining a clear structure and appropriate decision rights relative to data and information, is one of the key success factors, particularly in projects that span departmental and functional boundaries (Abbasi, Sarker, & Chiang, 2016). Procedural practices can include both formal and informal control mechanisms and are targeted in helping organizations trim wasteful spending and minimize bad big data-related choices. These include from what data will be gathered, stored, and analysed, to the skills of technical and business employees that are sought after in the market (Tallon et al., 2013). Procedural practices are vital in big data projects since they define how information governance is executed in different levels within the organization and at different inflection points of the information life cycle. Therefore, they constitute important elements of building a big data analytics capability since they determine the collective knowledge of the resources and their orchestration (Hashem et al., 2015). Finally, relational practices play a critical role in the formation of big data analytics capabilities since they define the roles and responsibilities of employees, and determine how they should be adapted based on organizational demands. Relational practices in the context of big data are responsible for aligning individuals with the goals of strategy. Within these practices are activities of building knowledge amongst employees, a critical aspect in maintaining a strong big data analytics capability. Based on this argumentation, we hypothesize that:

H1: *Information governance has a positive effect on big data analytics capability*

The share of companies that report using big data analytics to innovate is rising significantly (Ransbotham & Kiron, 2017). Organizations with strong big data analytics capabilities use these competences to innovate not only incrementally in existing operations, but also new processes, products, services, and even business models. Big data analytics has been shown to enable the identification and seizing of new business opportunities through the combination of diverse data sources (Ransbotham & Kiron, 2017). By coalescing data from various sources, insight can be generated that was previously unobtainable. When it comes to reconfiguring a firms existing mode of operation the effects can be realized through multiple ways (Kathuria, Saldanha, Khuntia, & Andrade Rojas, 2016). A big data analytics capability can prompt innovation in multiple ways. First, incremental improvements in existing products or services through more detailed identification of customer feedback and real-time operational monitoring can be attained through a strong big data analytics capability (H. Chen, Chiang, & Storey, 2012). A prominent example is that of Southwest airlines, that uses speech-analytics tools to record conversations between service personnel and extract insight that can lead to higher customer satisfaction. In this respect, a BDAC allows a firm to sense customer needs, seize opportunities that were previously not identified, and reconfigure existing ways of operating based on the insight that big data analytics indicates (Infotech, 2013). Similar effects of BDAC's on improving incremental innovative capabilities are described in a recent article in MIT Sloan Management Review, in which it is noted that firms that belonged in the forerunner group of deploying big data were more than 4 times more likely to introduce improvements to existing processes, products and services (Ransbotham & Kiron, 2017). In addition, a BDAC can help firms develop opportunities for radical innovations, by deploying new products or services that can create new markets and create fundamental changes in the market and consumer behaviour (Erevelles, Fukawa, & Swayne, 2016). Such applications are quickly being deployed in the healthcare sector where personalized medicine is being developed based on big data analytics of systems biology (e.g. genomics) with electronic health record data (Murdoch & Detsky, 2013). Based on the foregoing discussion we hypothesize that:

H2: *Big data analytics capabilities have a positive effect on incremental innovation capability*

H3: *Big data analytics capabilities have a positive effect on radical innovation capability*

While a BDAC may be important in driving both types of innovative capabilities, it is commonly acknowledged that companies that share data internally and have a shared vision of the role of analytics in strategy gain more (Ransbotham & Kiron, 2017). In addition, companies that are most innovative with analytics, according to recent reports, are more likely to share data beyond organizational boundaries. Strong information governance practices facilitate data sharing, which in turn amplifies the effect on innovation (Tan, Zhan, Ji, Ye, & Chang, 2015). A recent report from Deloitte, points out that the two dominant barriers for boards working with innovation are lack of insight (47%) and lack of organizational design to handle data-driven knowledge (46%) (Deloitte, 2016). As such, information governance exerts positive loopbacks when combined with a strong BDAC. A solid information governance needs to be more than a system of tactics to derive value, it must actually influence organizational behaviour and help strengthen the insight generated by a firms BDAC (McAfee et al., 2012). The main reason for this is because information governance dictates how data is shared, the quality of data and generated insights, as well as the formal procedures of communicating outcomes with executives of all domains (Lee, Kao, & Yang, 2014). Opening data and insight within and between organizations cannot work without structure, processes, and well-defined roles (Tallon et al., 2013). Information governance facilitates data sharing and decision making based on insight by controlling what can be shared and what cannot. In addition, good information governance schemes can improve both the effectiveness and speed with which shared data and analytics improve innovations (Ransbotham & Kiron, 2017). From the above argument we hypothesize that:

H4: *Information governance positively moderates the impact of big data analytics capabilities on incremental innovation capability*

H5: *Information governance positively moderates the impact of big data analytics capabilities on radical innovation capability*

4 Methods

4.1 Data

To empirically test the previously formulated research hypotheses, a survey instrument was developed and sent out to key informants within firms. As part of a pre-test, we conducted a small-cycle study with 24 firms to examine the statistical properties of the measures. The pre-testing procedure enabled us to assess the face and content validity of items and to ensure that key respondents would be in place to comprehend they survey as intended. For the main study, a population of approximately 1500 firms was used from a mailing list of Chief Information Officers and IT managers based in Greece. To ensure a collective response, the respondents were instructed to consult other employees within their firms for information that they were not knowledgeable about. The data collection process lasted for approximately three months (April 2017 – July 2017), and on average completion time of the survey was 14 minutes. A total of 193 firms started to complete the survey, with 175 providing complete responses.

Factors	**Sample (N = 175)**	**Percentage (%)**
Industry		
Bank & Financials	19	10.8%
Consumer Goods	17	9.7%
Oil & Gas	5	2.8%
Industrials (Construction & Industrial goods)	13	7.4%
ICT and Telecommunications	35	20.0%
Technology	16	9.1%
Media	13	7.4%
Transport	3	1.7%
Other (Shipping, Basic Materials, Consumer Services etc.)	54	30.8%
Firm size (Number of employees)		
1 – 9	34	19.4%
10 – 49	42	24.0%
50 – 249	53	30.2%
250+	46	26.2%
Respondent’s position		
CEO/President	23	13.1%
CIO	129	73.7%
Head of Digital Strategy	4	2.0%
Senior Vice President	6	3.4%
Director	6	3.4%
Manager	7	4.0%

Table 1. Sample Characteristics

Since non-response bias is common problem in such large-scale questionnaire studies, measures were taken both during the collection of the data to make sure we had a representative response rate, as well as after the concluding of the data gathering. Participants were provided with an incentive to partake in the study, and were given a personalized report benchmarking their firms’ performance in a number of functional areas to industry and country averages (Sax, Gilmartin, & Bryant, 2003). After the initial invitation to take part in the survey, respondents were re-contacted on three occasions with two-week interval between each reminder. When the data collection procedure was finalized, and to ensure that no bias existed within data, early and late responses were compared on construct level to make sure that no significant differences existed. Two groups of responses were constructed, those who replied within the first three weeks and those that replied in the final three weeks. By performing t-test comparisons between groups means no significant differences were observed. Furthermore, no significant differences were noted between responding and non-responding firms in terms of size and industry. Taking into consideration that all data were collected from a single source at one point in time, and that all data were perceptions of key respondents, we controlled for common method bias following the guidelines of Chang, Van Witteloostuijn, and Eden (2010). *Ex-ante*, respondents were assured that all information they provided would remain completely anonymous and confidential, and that any analysis would be done on an aggregate level for research purposes solely. *Ex-post*, Harman's one factor test was employed, which indicated that a single construct could not account for the majority of variance (Fuller, Simmering, Atinc, Atinc, & Babin, 2016).

4.2 Variable Definition and Measurement

Big Data Analytics Capability (BDAC) is defined in accordance with the study of Gupta and George (2016) as a firm's capability to assemble, integrate, and deploy its big data-based resources. This definition clearly distinguishes and separates the process of orchestrating big data-related resources from any performance outcomes. As such, BDAC is conceptualized and developed as a third-order formative construct. The three underlying pillars that comprise a BDAC are big data-related tangible, human skills, and intangible resource constructs, which in turn are formulated as second-order formative constructs, comprising of seven first-order constructs.

Information Governance (IG) is defined in line with the study of Tallon et al. (2013) as a collection of capabilities or practices for the creation, capture, valuation, storage, usage, control, access, archival, and deletion of information over its life cycle. This definition clearly highlights the two main goals of information governance which are to maximize the potential value of information to the organization by ensuring data quality, and to protect information so that its value to the organization is not lost. Using the framework of Peterson (2004), and building on related work on information governance (Tallon et al., 2013), three pillars are identified and quantified. These include structural, procedural, and relational practices. As such, IG is conceptualized and developed as a second-order formative construct. The three underlying pillars that comprise a IG are formulated as first-order reflective constructs. Previous studies were utilized to identify and develop the measurement scale for each of the underlying dimensions (Tallon et al., 2013; Weber et al., 2009) and a pre-test with a number of experts and a small cycle study were conducted to verify the validity and reliability of corresponding items..

Innovative Capability (IC). An innovative capability is regarded as a type of dynamic capability and is defined in the context of the skills and knowledge needed to effectively absorb, master and improve existing technologies, products and to create new ones (Romijn & Albaladejo, 2002). We measured innovative capability through two first-order latent construct; *incremental innovative capability* (INC) and *radical innovative capability* (RAD). Incremental innovative capability was measured with three indicators assessing an organizations capability to reinforce and extend its existing expertise and product/service lines. Likewise, radical innovative capability was assessed through three indicators that asked respondents to evaluate their organization's ability to make current product/service lines obsolete (Subramaniam & Youndt, 2005).

5 Analysis and Results

To validate the measurement model and test the hypothesized relationships, we used partial least squares (PLS), a second-generation structural equation modeling (SEM) technique. Specifically, the software package SmartPLS 3 was used to conduct all analyses (Ringle, Wende, & Becker, 2015). PLS-SEM is considered as an appropriate methodology for this study since it permits the simultaneous estimation of multiple causal relationships between one or more independent variables, and one or more dependent variables (Hair, Ringle, & Sarstedt, 2011).

5.1 Measurement Model

Since the model contains both reflective and formative constructs, we used different assessment criteria to evaluate each. For first-order reflective latent constructs we conducted reliability, convergent validity, and discriminant validity tests. Reliability was examined at the construct and item level. At the construct level we assessed Composite Reliability (CR), and Cronbach Alpha (CA) values, and established that their values were above the threshold of 0.70 (Nunnally, 1978). Indicator reliability was assessed by examining if construct-to-item loadings were above the threshold of 0.70. To assess convergent validity, we examined if AVE values were above the lower limit of 0.50, with the lowest observed value being 0.56 which greatly exceeds this threshold. Discriminant validity was established through three means. The first looked at each constructs AVE square root in order to verify that it is greater than its highest correlation with any other construct (Fornell-Larcker criterion). The second tested if each indicators outer loading was greater that its cross-loadings with other constructs (Farrell, 2010). Recently, Henseler, Ringle, and Sarstedt (2015) argued that a new criterion called the Heterotrait-Monotrait ratio (HTMT) is a better assessment indicator of discriminant validity. The HTMT is calculated based on the average of the correlations of indicators across constructs measuring different aspects of the model, relative to the average of the correlations of indicators within the same construct. Values below 0.85 are an indication of sufficient discriminant validity, hence, the obtained results confirm discriminant validity. The abovementioned results (Table 2) suggest that first-order reflective measures are valid to work with and support the appropriateness of all items as good indicators for their respective constructs (Ruiz, Gremler, Washburn, & Carrión, 2008).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) Data	**n/a**											
(2) Basic Resources	0.49	**n/a**										
(3) Technology	0.53	0.64	**n/a**									
(4) Managerial Skills	0.54	0.53	0.49	**0.91**								
(5) Technical Skills	0.45	0.62	0.57	0.68	**0.88**							
(6) Data-driven Culture	0.51	0.49	0.45	0.49	0.45	**0.87**						
(7) Organizational Learning	0.50	0.46	0.47	0.71	0.53	0.55	**0.94**					
(8) Structural Governance	0.51	0.38	0.34	0.54	0.39	0.55	0.42	**0.90**				
(9) Procedural Governance	0.50	0.59	0.55	0.67	0.50	0.54	0.67	0.58	**0.83**			
(10) Relational Governance	0.42	0.39	0.48	0.61	0.49	0.46	0.51	0.67	0.56	**0.93**		
(11) Incremental Innovation	0.45	0.53	0.50	0.61	0.61	0.52	0.62	0.51	0.51	0.57	**0.93**	
(12) Radical Innovation	0.42	0.47	0.45	0.55	0.48	0.53	0.53	0.54	0.42	0.58	0.82	**0.96**
Mean	4.98	4.79	4.61	5.07	4.51	5.01	5.17	4.45	5.03	4.10	4.10	4.32
Standard Deviation	1.72	1.74	2.02	1.84	1.82	1.81	1.50	1.95	1.82	1.51	1.53	1.79
AVE	n/a	n/a	n/a	0.82	0.77	0.75	0.89	0.81	0.68	0.86	0.86	0.93
Cronbach's Alpha	n/a	n/a	n/a	0.93	0.90	0.83	0.96	0.76	0.88	0.84	0.92	0.96
Composite Reliability	n/a	n/a	n/a	0.95	0.93	0.90	0.97	0.89	0.91	0.92	0.95	0.97

Table 2. Assessment of reliability, convergent and discriminant validity of reflective constructs

For formative indicators, we first examined the weights and significance of their association with their respective construct. All first-order constructs the items had positive and highly significant effects. Next, to evaluate the validity of the items of formative constructs, we followed MacKenzie, Podsakoff, and Podsakoff (2011) and Schmiedel, Vom Brocke, and Recker (2014) guidelines using Edwards (2001) adequacy coefficient (R^2_a). To do so we summed the squared correlations between formative items and their respective formative construct and then divided the sum by the number of indicators. All R^2_a value exceeded the threshold of 0.50 (Table 3), suggesting that the majority of variance in the indicators is shared with the overarching construct, and that the indicators are valid representations of the construct. Similarly, for the higher-order constructs, we first examined the weights of the formative lower-order constructs on their higher-order constructs (five second-order constructs and one third-order construct). All weights were significant, and the results Edward adequacy coefficient for each was again greater than the limit of 0.50 (Edwards, 2001). Next, we examined the extent to which the indicators of formative constructs presented multicollinearity. Variance Inflation Factor (VIF) values below 10 suggest low multicollinearity, however, a more restrictive cut-off of 3.3 is used for formative constructs (Petter, Straub, & Rai, 2007). All values of first-order, second-order, and third-order constructs were below the threshold of 3.3 indicating an absence of mutlicollinearity.

Construct	Measures	Weight	Significance	VIF	R^2_a
Data	D1	0.383	p<0.001	2.800	0.79
	D2	0.287	p<0.001	1.300	
	D3	0.552	p<0.001	1.112	
Basic Resources	BR1	0.584	p<0.001	2.890	0.74
	BR2	0.496	p<0.001	2.428	
Technology	T1	0.209	p<0.001	2.256	0.76
	T2	0.398	p<0.001	1.986	
	T3	0.358	p<0.001	2.285	
	T4	0.202	p<0.001	2.129	
	T5	0.552	p<0.001	2.030	
Tangible	Data	0.324	p<0.001	1.471	0.84
	Basic Resources	0.311	p<0.001	1.788	
	Technology	0.541	p<0.001	1.900	
Human	Managerial Skills	0.572	p<0.001	1.847	0.89
	Technical Skills	0.520	p<0.001	1.847	
Intangible	Data-driven Culture	0.389	p<0.001	1.443	0.91
	Organizational Learning	0.731	p<0.001	1.443	
BDAC	Tangible	0.340	p<0.001	2.108	0.90
	Human	0.429	p<0.001	2.447	
	Intangible	0.358	p<0.001	2.161	
Information Governance	Structural	0.261	p<0.001	2.064	0.88
	Procedural	0.605	p<0.001	1.636	
	Relational	0.290	p<0.001	1.977	

Table 3. Higher-order construct validation

5.2 Structural Model

The structural model from the PLS analysis is summarized in Figure 2, where the explained variance of endogenous variables (R^2) and the standardized path coefficients (*β)* are presented. Contrary to covariance structure analysis modelling approaches that are based on goodness-of-fit measures to assess the structural model, in PLS, the structural model is verified by examining coefficient of determination (R^2) values, predictive relevance (Stone-Geisser Q^2), and the effect size of path coefficients. The significance of estimates (t-statistics) are obtained by performing a bootstrap analysis with 5000 resamples. As depicted in Figure 2, both direct hypotheses were empirically supported. A firms' big data analytics capability is found to have a positive and significant impact on both incremental innovative capability (β=0.571, t=6.068, $p < 0.001$), and radical innovative capability (β=0.476, t=4.865, $p < 0.001$). In addition, information governance is found to exert a positive and significant effect on a firm's big data analytics capability (β=0.595, t=10.862, $p < 0.001$). With regard to the moderating effect on information governance, it is found to has a positive and significant influence when it comes to radical innovative capability (β=0.189, t=2.105, $p < 0.05$), nevertheless, in relation to a firm's incremental innovative capability the impact is non-significant (β=0.091, t=0.865, $p > 0.05$). The structural model explains 42.3% of variance for dynamic capabilities (R^2 = 0.423), 52.4% for incremental innovative capabilities (R^2 = 0.524) and 42.5% for radical innovative capabilities (R^2 = 0.425). These coefficients of determination represent moderate to substantial predictive power (Hair Jr & Hult, 2016).

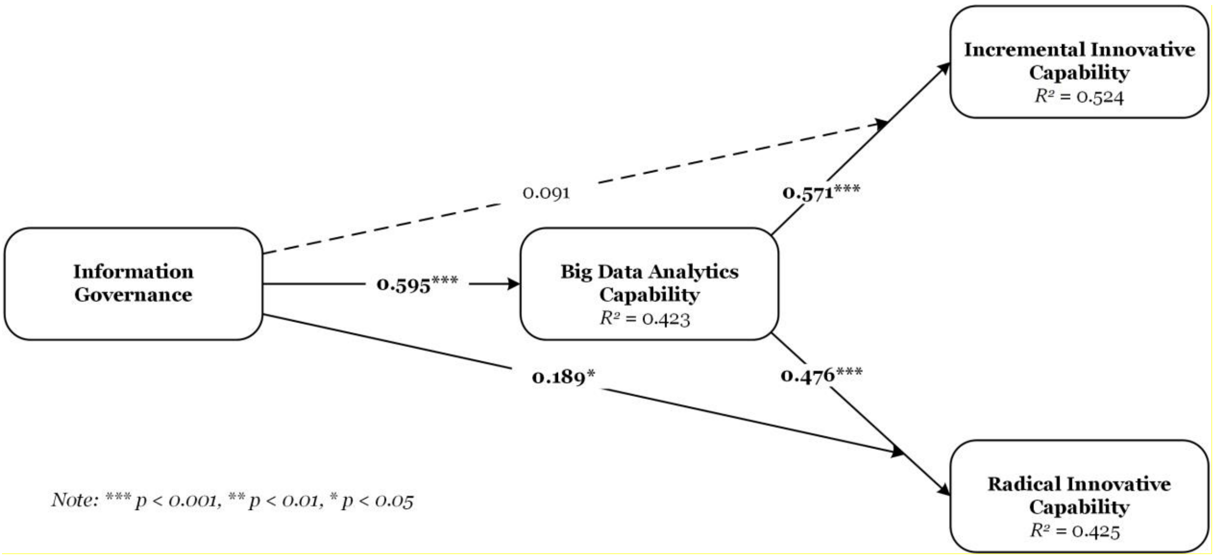

Figure 1. Estimated causal relationships of structural model

6 Discussion

Despite the hype around big data continuously growing, the mechanisms and conditions through which innovation can be enhanced still remain an under-explored part of research. To address this gap, we build on two core aspects of big data, information and big data analytics capability. Grounded on the RBV and on past empirical work in the broader domain of IS studies, we examine the complementarities and dependencies that characterize the relationship between information governance and a firm's big data analytics capability. We utilized primary survey data from 175 high-level executives, and employed PLS-SEM analysis to examine our hypothesized relationships.

Specifically, we examine if a big data analytics capability can help develop two important, but distinct, types of innovative capabilities, radical and innovative. In addition, we explore the role of information governance in helping develop a firm's big data analytics capability, as well as the amplifying effect of a well-establish governance scheme in translating insight into innovation output. By doing so, we add to the emerging literature on the importance of information governance in the big data era, and the criticality of establishing a robust scheme for maturing a firm's big data analytics capability, but also for harnessing the insight into action. Furthermore, this study extends existing research on the importance of a big data analytics capability, and demonstrates through a large-scale empirical study that the impact of a BDAC can be quantifiable on innovation-related output. While there is significant anecdotal evidence on the role of a BDAC on accelerating a firm's innovative capability, there is very limited theoretically grounded research to verify such a relationship. In fact, the outcomes of our study show that a BDAC helps augment both an incremental and a radical innovative capability. The under-explored role of information governance is also examined in this association. Our results show that while information governance may not have any substantial influence in amplifying insight towards incremental innovative capabilities, it plays an important part in accelerating the formation of a firm's radical innovative capability. This outcome can be justified by the fact that most radical innovations stem from cross-organizational partnerships, and in such cases establishing a solid information governance is of paramount importance. What may differentiate forerunners from laggards in the game of competitiveness, can well be the realization of the significance of introducing well-defined structural, procedural, and relational practices when it comes to big data analytics.

6.1 Practical Implications

The present study also raises some interesting findings that can be applicable in practice. Since our conception of big data analytics capabilities includes, not only technical resources, but also human skills and intangible ones, this study confirms the importance of placing an equal amount of emphasis on the broader picture when it comes to big data. It is quite common in organizations to see big data as a purely technical task, involved with databases, data collection and curating, and applying sophisticated analytic algorithms and techniques. While this is true, it is important for managers to understand that the main issue in deriving any business value is not so much the technical issues, but embedding these technologies into the organizational fabric. This requires investing in resources that are not purely technical, such as human skills, and establishing a data-driven culture and continuous learning. Yet, to do so, our findings indicate that a starting point should be the development of an information governance scheme. By clearly defining the important structures processes, and roles, the deficiencies can be easily spotted and targeted investments can be made. In addition, an information governance provides a sense of direction in terms of who does what, and what belongs to who. This is an important element in infusing data-driven logic into the organization, and to break down the impression that is very common in many firms, that big data analytics is a purely technical task. The significance of information governance not only is vital is forming a strong big data analytics capability, but is particularly relevant in deriving value out of any investments. Based on the results of our study, it is clear that under well-defined information governance schemes, the value of a big data analytics capability towards deriving radical innovation capabilities is amplified. This has great significance for higher-level executives since radical innovations have the potential to generate competitive success if exploited swiftly.

6.2 Limitations and Future Work

Despite the contributions of the present study it is constrained by a number of limitations that future research should seek to address. First, as noted already, self-reported data are used to test our research hypotheses. Although considerable efforts were undertaken to confirm data quality, the potential of biases cannot be excluded. The perceptual nature of the data, in conjunction with the use of a single key informant, could suggest that there is bias, and that factual data do not coincide with respondents' perceptions. Although this study relies on top management respondents as key informants, sampling multiple respondents within a single firm would be useful to check for inter-rater validity and to improve internal validity. Second, although we examine the value of big data analytics capabilities on a firm's innovative capabilities, we do not factor in the influence of the external environment. It is highly likely that the value of directing big data initiatives may be more or less beneficial in different conditions. This is an area that future research should seek to address and it is of increased practical value, particularly considering the costs of deploying big data initiatives. The main argument that a big data analytics capability is necessary but not a sufficient condition to lead to competitive performance gains remains subject to several internal and external factors, which hopefully will be addressed in subsequent research studies.

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Appendix A. Survey Instrument

Measure	Item	S.D.
Big Data Analytics Capability		
Tangible		
- Data	D1. We have access to very large, unstructured, or fast-moving data for analysis	1.66
	D2. We integrate data from multiple sources into a data warehouse for easy access	1.46
	D3. We integrate external data with internal to facilitate analysis of business environment	1.49
- Basic	BR1. Our 'big data analytics' projects are adequately funded	1.46
Resources	BR2. Our 'big data analytics' projects are given enough time to achieve their objectives	1.47
- Technology	T1. We have explored or adopted parallel computing approaches (e.g., Hadoop) to big data processing	2.02
	T2. We have explored or adopted different data visualization tools	1.64
	T3. We have explored or adopted new forms of databases such as Not Only SQL(NoSQL)	2.03
	T4. We have explored or adopted cloud-based services for processing data and performing analytics	2.08
	T5. We have explored or adopted open-source software for big data analytics	2.00
Human Skills		
- Managerial Skills	MS1. Our BDA managers are able to understand the business need of other functional managers, suppliers, and customers to determine opportunities that big data might bring to our business.	1.43
	MS2. Our DBA managers are able to coordinate big data-related activities in ways that support other functional managers, suppliers, and customers	1.44
	MS3. Our BDA' managers are able to understand and evaluate the output extracted from big data	1.29
	MS4. Our BDA' managers are able to understand where to apple big data	1.25
- Technical Skills	TS1. Our 'big data analytics' staff has the right skills to accomplish their jobs successfully	1.51
	TS2. Our 'big data analytics' staff is well trained	1.51
	TS3. We provide big data analytics training to our own employees	1.64
	TS4. Our 'big data analytics' staff has suitable education to fulfil their jobs	1.61
Intangible		
- Data-driven	DD1. We base our decisions on data rather than on instinct	1.60
- Culture	DD2. We are willing to override our own intuition when data contradict our viewpoints	1.46
	DD3. We continuously coach our employees to make decisions based on data	1.58
- Organizational	OL1. We are able to acquire new and relevant knowledge	
Learning	OL2. We have made concerted efforts for the exploitation of existing competencies and exploration of new knowledge	1.32
	OL3. We are able to assimilate relevant knowledge	1.35
	OL4. We are able to apply relevant knowledge	1.25
Information Governance		
Structural Practices	In our organization, we ___________________	
	STR1. have identified key IT and non-IT decision makers to have the responsibility regarding data ownership, value analysis and cost management.	1.74
	STR2. use steering committees to oversee and assess data values and costs	1.67
Procedural Practices	In our organization, we have controlled practices regarding data management in terms of ___________________	1.71
	PCR1. setting retention policies (e.g. time to live) of data	1.25
	PCR2. backup routines	1.66
	PCR3. establishing/monitoring access (e.g. user access) to data	1.51
	PCR4. classifying data according to value	1.52
	PCR5. monitoring costs versus value of data	1.56
Relational Practices	In our organization, we ___________________	
	RLT1. educate users and non-IT managers regarding storage utilization and costs	1.66
	RLT2. develop communications regarding policy effectiveness and user needs	1.37
Innovative Capability	How would you rate your organizations capability to generate the following types of innovations in the products/services you introduce	
Incremental	INC1. Innovations that reinforce our prevailing product/service lines	1.31
	INC2. Innovations that reinforce our existing expertise in prevailing products/services	1.21
	INC3. Innovations that reinforce how you currently compete	1.36
Radical	RAD1. Innovations that make our prevailing product/service lines obsolete	1.32
	RAD2. Innovations that fundamentally change our prevailing products/services	1.34
	RAD3. Innovations that make our expertise in prevailing products/services obsolete	1.34