Information & Management 57 (2020) 103361

Contents lists available at ScienceDirect

Information & Management

journal homepage: www.elsevier.com/locate/im

The role of information governance in big data analytics driven innovation

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ARTICLE INFO

Keywords:
Big data analytics capabilities
Information governance
Incremental innovation
Radical innovation
Environmental uncertainty
FIMIX-PLS

ABSTRACT

The age of big data analytics is now here, with companies increasingly investing in big data initiatives to foster innovation and outperform competition. Nevertheless, while researchers and practitioners started to examine the shifts that these technologies entail and their overall business value, it is still unclear whether and under what conditions they drive innovation. To address this gap, this study draws on the resource-based view (RBV) of the firm and information governance theory to explore the interplay between a firm's big data analytics capabilities (BDACs) and their information governance practices in shaping innovation capabilities. We argue that a firm's BDAC helps enhance two distinct types of innovative capabilities, incremental and radical capabilities, and that information governance positively moderates this relationship. To examine our research model, we analyzed survey data collected from 175 IT and business managers. Results from partial least squares structural equation modelling analysis reveal that BDACs have a positive and significant effect on both incremental and radical innovative capabilities. Our analysis also highlights the important role of information governance, as it positively moderates the relationship between BDAC's and a firm's radical innovative capability, while there is a nonsignificant moderating effect for incremental innovation capabilities. Finally, we examine the effect of environmental uncertainty conditions in our model and find that information governance and BDACs have amplified effects under conditions of high environmental dynamism.

1. Introduction

The past few years have seen a large number of studies examining the effects that big data analytics have on firm performance outcomes [1,2]. Nevertheless, there is substantially less research examining if and under what conditions big data analytics can help firms become more innovative [3]. A number of early studies have claimed that big data analytics can be the next frontier of innovation [4], while some later reports have documented that firms are already utilizing big data analytics toward the enhancement of existing products and services, and as a tool for the creation of radically new ones [5]. A study by Ransbotham and Kiron [6] noted that early adopters of big data analytics managed to deliver more incremental innovation in their existing products and services, while also being able to generate more radical innovations at the same time by introducing fundamentally new products, services, and business models. Despite these promising findings, a recent report by Gartner [7] indicates that the vast majority of such initiatives will likely fail to deliver business value simply because big data analytics projects are not scaled in a systematic way in the organization. As innovation is consistently ranked as one of the top priorities of business executives [8], knowing if and how big data analytics can contribute to a competitive edge in terms of driving innovation is critical for managers and practitioners. In addition, as big data analytics projects entail large associated costs, it is important to identify what types of outcomes they can deliver and how to optimally achieve such targets to avoid investments that do not pay off [9].

When it comes to strengthening a firm's innovation capabilities, the literature has argued that a structured adoption of big data analytics coupled with a robust information governance scheme are prerequisites of success [10]. These two pillars, presented under the notions of big data analytics capabilities (BDACs) [1], and information governance [11], respectively, have emerged as a core area of research focus. The literature on BDAC suggests that firms that manage to develop important resources pertinent to big data analytics are more likely to realize performance gains. Nevertheless, it is still unclear whether BDAC can result in such performance outcomes simply by improving operational efficiency of firms and their adaptability or by also making them more innovative [12]. This leaves practitioners in unchartered territories when faced with implementing such investments in their firms and particularly when attempting to leverage their BDAC to strengthen their innovation capabilities [13].

Adding to the above, rapid data growth has rendered information

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https://doi.org/10.1016/j.im.2020.103361
Received 25 December 2019; Received in revised form 7 August 2020; Accepted 12 August 2020
Available online 16 August 2020

governance as a top issue for senior IT and business management when designing their big data projects [14]. Most research to date operates under the assumption that simply because firms have invested in a bundle of big data analytics resources, they will be able to leverage the information artifact and transform it into meaningful and actionable insight [15]. Nevertheless, practitioner reports as well as exploratory studies have shown that firms struggle with different forms of problems relating to the information artifact [15]. These issues range from having siloed business units where information is not accessible, not having clear rules about how data and information should be processed and what are the ownership rights, as well as having opaque processes regarding information manipulation and insight generation ([2,15]). However, there is to date limited knowledge regarding the inter-dependencies between structured adoption of big data analytics and information governance, particularly in relation to innovation outcomes. In addition, there is a prevailing assumption that big data analytics can be of greater value in relation to innovation outcomes under conditions of high environmental uncertainty [6]. According to this reasoning, big data analytics enable firms to analyze and make sense of large amounts of data in highly complex, fast-paced, and volatile conditions, where it would be impossible to do so otherwise [16].

Building on the foregoing discussion, this study seeks to explore if BDACs can enable firms to strengthen their innovation capabilities as well as what are the complementary, moderating effects of information governance in these associations. We distinguish between two types of innovation capabilities, namely incremental and radical process innovation capabilities. Incremental innovation capabilities are concerned with improvements in existing products and services, whereas radical innovation capabilities are focused on fundamentally new products, markets, and business models [17]. Being able to sustain both incremental and radical innovation capabilities has long been documented as a key circumstance for sustained success [18]. We argue that structured adoption of big data analytics in the form of BDACs will lead to enhanced incremental and radical innovation capabilities, which will be amplified under the presence of information governance practices. In examining these associations, we also factor in the effect of environmental uncertainty variables to investigate how the external environment conditions the previously mentioned effects, differentiating as such between dynamism, heterogeneity, and hostility. Hence, we motivate our study on the following research questions:

RQ1. *What is the effect of a firm's BDACs on incremental and radical innovation capabilities, and how does information governance moderate these relationships?*

RQ2. *How does the external environment condition these direct and moderated associations?*

To answer the first research question, we ground this study on the resource-based view (RBV) of the firm, which is used to define a BDAC and the relevant resources for enhancing a firm's innovation capabilities [1]. We then adopt an information governance theory lens to examine the moderating effects that information governance practices have on the relationships between BDACs and incremental and radical innovation capabilities [11]. We posit that establishing information governance practices amplifies the effects of a BDAC on innovation capabilities due to increased transparency in relation to the available data resources, the clarity in ownership, and thus the use of information as well as on the increased permeability of firm unit boundaries, which allows for cross-functional collaboration on information resources [19]. Our second research question builds on the argument that information processing capacities, in the form of BDACs and information governance practices, will produce increased effects under conditions where there is high complexity, turbulence, and velocity, and thus information processing capacities and data-driven insight are most required [20].

The rest of the paper is structured as follows. In the next section, we introduce the notion of a BDAC grounded on the RBV of the firm, and then proceed to define information governance based on information governance theory. We then proceed to hypothesize on the effect of BDACs on a firm's incremental and radical innovation capabilities and how the presence of information governance practices amplifies these associations. In sequence, we postulate on the effect of environmental uncertainty conditions on these associations. To empirically examine these hypotheses, we develop a survey-based study and in the Methods section describe the data collection procedures and measures that we use to operationalize these concepts. 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

2.1. Big data analytics capabilities

Managing to build and sustain a competitive advantage is one of the areas of focus of strategic management literature [21]. Within this body of research, the RBV has been one of the most promising theoretical perspectives in management and IS literature. In essence, the RBV attempts to explain how firms achieve and sustain a competitive advantage through the resources they own or manage [22,23]. The RBV has also been an instrumental theoretical perspective in explaining how firms foster their innovation capabilities, thus providing a theoretically grounded link between the resources of a firm and its ability to innovate [24]. In identifying the types of resources that a firm must manage, Grant [25] proposed a distinction between tangible (financial and physical resources), human skills (employees' knowledge and skills), or intangible (learning propensity and organizational culture). Following this approach, studies in the domain of big data analytics have adopted the same categorization of resources in an attempt to define the relevant resources that jointly form a firm's BDAC ([1,3]). Research in this stream now recognizes that big data analytics go beyond technologies and data and require investments in several other key areas to derive value [1].

The notion of a BDAC has grown out of a large body of research studies looking into the obstacles that organizations face when implementing big data projects [1,26,27]. In information systems (IS) research, there is growing consensus that value form big data analytics projects does not occur only because of the data and the analytical tools and processes, but includes complimentary resources that need to be fostered [28]. The notion of BDAC has been suggested to encompass the various resources that organizations must develop to derive value from big data analytics [1,29]. A BDAC has been defined as the ability of a firm to capture and analyze data toward the generation of insights by effectively orchestrating and deploying its data, technology, and talent [30,31]. While several definitions have been proposed so far, some focus on the necessary processes that must be put in place to leverage big data [32,33], while others emphasize on the investment of necessary resources and their alignment with strategy [34]. In essence, the notion of BDAC extends the view of big data to include all related organizational resources that are important in leveraging big data to their full strategic potential [35].

Building the classification framework proposed by Grant [25], big data-related tangible resources include, data, technology, and basic resources [1]. In the context of developing a BDAC, one of the central resources are the data an organization has access to. What distinguishes big data are its volume, variety, velocity, and veracity [14], yet, it is frequently mentioned that IT strategists and data analysts are concerned with the quality and availability of the data they analyze [36,37]. Big data, nevertheless, also call for novel technologies that are able to handle large amounts of diverse and fast-moving data [1]. As such data are often unstructured and high in volume, it requires sophisticated infrastructure investments to derive meaningful and valuable insight [27]. In addition, basic resources in the form of financial support and time are fundamental, as projects may not start yielding any visible results immediately [1]. When it comes to human skills, literature recognizes that both technical and managerial-oriented skills are required to derive value from big data investments [29]. Although 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 [38]. Finally, in relation to intangible resources, a data-driven culture and organizational learning are noted as being critical aspects of effective deployment of big data initiatives [14]. An organizational culture that favors data-driven decision-making has been argued as being a key factor in determining the overall success and continuation of big data analytics projects [39]. In addition to this, and because of the constantly changing technological landscape, it is imperative that organizations adopt a vision where continuous learning is promoted [27]. This intangible resource allows for continuous adaptation and renewal of big data competences and contributes to overall business value.

Although empirical studies that examine the business value of developing a BDAC have only started to emerge recently, some early research has found positive effects on organizational outcomes. In their empirical study, Gupta and George [1] show that a BDAC has a positive and significant effect on a firm's market and operational performance. Wamba et al. [29] show that firms that foster their BDACs realize positive returns on firm performance directly, and indirectly, through a mediated effect on process-oriented dynamic capabilities. Similar results are noted by Mikalef et al. [40] who find that BDACs enable firms to revamp their operational capabilities, which result in a better fit to the environment and subsequently to competitive performance gains. Ransbotham and Kiron [6] find that companies that are early adopters of big data analytics are more inclined to produce incremental innovations in their existing products and services, and also to radically innovate, introducing all-new products, services, and business models. While these are just some of the early studies that suggest a positive impact of BDACs on performance indicators, there is still little empirical evidence linking a firm's structured adoption in big data analytics with enhanced abilities to innovate. Understanding if and what types of innovation capabilities BDACs can support is important for practitioners to initiate and target their investments accordingly. Furthermore, understanding what resources they must invest in to realize such gains is of high practical relevance, as recent reports indicate that many big data analytics projects often do not make it to production and fail to deliver expected outcomes [7].

2.2. Information governance

Despite the importance of investing on the relevant resources that jointly comprise a BDAC, there is a broad assumption that doing so is a sufficient condition to realize performance gains. While fostering a BDAC is a necessary condition for realizing performance gains, it is not a sufficient condition for realizing the full value that data-generated insight can deliver [15]. Both researchers and practitioners now recognize that data-generated insight is limited by the data that are available for input as well as the processes, structures, and role assignments that are assigned around the information artifact, which dictate what information is available for analyzing and how visible it is. This provides an alternative view on big data, which emphasizes the importance of governance as the mechanism of orchestrating resources into valuable business-enhancing capabilities [41]. In the broader domain of IT management, past studies have found that firms that manage to establish a robust IT governance scheme, are more likely to outperform their competitions [42–44]. Following the rapid growth in interest in big data analytics, the focus has now shifted to a subset of IT governance, information governance, which dictates who manages the information artifact and how exactly it is created, stored, processed, and accessed within and throughout organizational boundaries [11]. This increase of interest has led to a theory of information governance, which distinguishes its main pillars as well as its antecedents and consequences [11].

Information governance is, therefore, defined as *a collection of competences or practices for the creation, capture, valuation, storage, usage, control, access, archival, and the deletion of information and related resources over its life cycle* ([45,3,11]). Since there are several dimensions pertinent to the governance of IT, Weber et al. [46] argue that information governance should encompasses activities relating to decision-maker roles (structural practices), decision tasks (procedural practices), and person responsibilities and development (relational practices) [15]. 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 [47]. Operational practices are oriented towards the processes and ways by which organizations execute information governance. These practices include a number of different tasks including data migration, data retention, cost allocation, data analytic procedures, and access rights. Nevertheless, the aforementioned practices can differ depending on the type of data that is analyzed or the type of insight that is being explored [48]. Finally, relational practices have to do with formalizing links between employees of the technical and business sides and how to establish efficient and effective communication and collaboration channels. They include practices and methods for knowledge sharing, education and training, and strategic planning [49,50].

The main discussion around the importance of information governance is that as resources need to be mobilized and utilized through structures, processes, and roles to deliver business value [51], so does the information artifact need to be orchestrated and leveraged accordingly to derive meaningful insight. This argument is becoming increasingly clear in the light of reports from practitioners citing a lack of access to key information, unclear processes, and ownership concerning the information artifact as well as distrust toward outcomes of analytics due to opaque and not explicitly defined processes of cleansing and transforming data into insight [26]. With the big data becoming increasingly more embedded in firm strategy, the role of information governance has managed to re-attract interest, particularly in its role as a mechanism for orchestrating resources into strong BDACs and translating insight into action (LaValle, et al., 2011). Nevertheless, to date there is limited knowledge on the impact that information governance has on moderating the effects of a firm's BDAC, and particularly how the presence of information governance practices may positively condition the emergence of innovation capabilities. This is particularly important when considering the large number of firms that adopt big data technologies without having established any form of governance to support such investments toward strategic outcomes. In particular, firms are driven toward adopting big data analytics with the aim of enhancing their incremental and radical innovation capabilities [6], yet the main challenges faced in achieving such outcomes are most commonly related to organizational and not technological aspects [9]. Hence, in the next section, we hypothesize about how the presence of information governance practices may enable firms to amplify the value they derive from their BDACs, particularly in relation toward the development of incremental and radical innovation capabilities.

2.3. Innovation capabilities

It is commonly accepted that a firm's ability to innovate is directly related to its intellectual capital or its capacity to leverage knowledge resources [52]. Although the link between organizational knowledge and innovation is well-established, there is still a limited understanding about how the different types of innovation capabilities emerge drawing on this knowledge [53]. The literature has therefore drawn a distinction between two broad types of innovation capabilities, which are seen as central in achieving and sustaining competitive performance gains: incremental and radical innovation capabilities [54]. Incremental innovation capabilities are those that are targeted in producing minor changes and modifications to products and technologies. Radical innovation capabilities on the other hand present major departures from existing ways of conducting business and constitute the basis for completely new products and services [17]. While incremental innovation capabilities enable organizations to achieve higher levels of efficiency, radical innovation capabilities are required to avoid generating competence traps [18]. As such, it has been argued that firms must aim to achieve a balance between their ability to exploit existing knowledge and explore new possibilities to remain competitive in the long run [55]. Being able to do so, however, requires that organizations foster mechanisms for enhancing both their incremental and radical innovation capabilities.

While there has been a considerable amount of research examining the different ways through which incremental and radical innovation capabilities are enhanced in the organizational setting [18,52], there is still a lack of understanding regarding the extent to which big data analytics investments can enhance each type of innovation capability. Even more, the role of information governance as the mechanism for mobilizing and orchestrating the data resource has been largely neglected in empirical studies. Past studies in the broader organizational domain have indicated that the governance structure firms adopt has an impact on extent and types of innovation capabilities that emerge [56]. Nevertheless, the conditioning effect that information governance may have in the context of big data analytics, particularly under varying external environmental conditions, is still a topic that has received limited attention. Knowing under what conditions big data analytics can enhance incremental and radical innovation capabilities, and the role that information governance has in enabling such outcomes is imperative when considering the significance that such investments have in contemporary enterprises. Furthermore, while there have been several practice-focused publications underscoring the potential of big data analytics as an enabler of innovation [4], there is little empirical evidence to consolidate such claims and provide practical guidelines about how incremental and radical innovation capabilities can be attained.

3. Research model

Our research model as depicted in Fig. 1 builds on the argument that to realize positive effects on their incremental and radical innovation capabilities, firms must follow a structured approach when adopting big data analytics, and thus invest in all relevant resources. We build on past empirical research that is grounded on the RBV and term this capacity as a BDAC and argue that it will have a positive association with both incremental and radical innovation capabilities. In addition, we postulate that while BDAC may be a contributor toward innovation outcomes, it is only under the presence of information governance practices that the full effects of BDACs can be realized. Therefore, BDACs and information governance are suggested to develop complementary effects in the emergence of incremental and radical capabilities. We also factor in the effect of environmental conditions and suggest that the effect of BDACs on innovation as well as the significance of information governance is augmented under uncertain external conditions.

3.1. Big data analytics capabilities as enablers of innovation

The share of companies that report using big data analytics to innovate is rising significantly over last few years [6]. Organizations with strong BDACs have been suggested to use these competences to innovate not only toward incremental innovation by enhancing existing products and services, but also toward new processes, products, services, and even business models [6]. Incremental and radical innovation are two distinct types of capabilities that are typically built by different resource configurations and provide a different effect in relation to the functioning, and performance objectives of the firm. Tushman and Romanelli [57], as well as several other researchers identify as incremental changes those that encourage the existing status, whereas radical changes are those where reorientation is prioritized, and patterns of consistency are fundamentally reordered. Hence. incremental innovations concern minor changes and slight alterations to existing products and services, whereas radical innovations represent significant transformations of existing capabilities in the firm and help develop completely new products and services [56]. To remain successful over a long period, it is argued that firms should aim to achieve an ambidextrous approach and to develop mechanisms that allow incremental and radical innovation capabilities to coexist at the same time [55]. Although high levels of efficiency can be achieved as a result of strong incremental innovative capabilities, radical innovation capabilities are necessary to avoid generating competence traps [18].

Big data analytics has been found to facilitate the identification of new and emerging business opportunities by combining diverse data sources [6]. Through a process of coalescing data from various sources, organizations can generate insight that was previously unobtainable. Reconfiguring a firms existing mode of operation based on such insight can be realized through several different ways [58]. 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 [59]. Several studies have shown that when aligned with strategy, big data analytics can be used to support real-time monitoring of customer feedback and to identify sentiment and response to specific organizational actions [60]. Such input can serve to revise or refine existing products or services, thus improving a firm's capability to introduce incremental innovations. Prominent examples of applying firm-wide BDACs to foster incremental innovation capabilities are found in several industries including those of retail ([61,62]) and tourism [60]. Similar effects of BDACs on improving incremental innovative capabilities are described in a recent article where it is suggested that organizations that belonged to the innovator group of deploying big data were more than four times more likely to introduce improvements to existing processes, products, and services [6]. Conboy et al. [63] through eight case studies demonstrate the different ways through which big data analytics can allow firms to sense emerging opportunities and threats and reconfigure their product and service offerings accordingly. For instance, they report on how banks can utilize big data such as transaction data and other customer profiling data to offer personalized services and offerings to their customers, therefore delivering incremental innovations in the form of marketing services. Similar effects are noted in terms of predictive maintenance and internet service provider products, where data from several different sources are leveraged to deliver improved services to customers.

Nevertheless, 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 behavior [64]. An array of such applications is currently being assimilated in the healthcare sector. An example application is the development of personalized medicine based on big data analytics of systems biology (e.g., genomics) in combination with data from electronic health records [65]. Furthermore, data and insight generated from existing products or services can open up avenues for completely new ones. For instance, in their report, Ransbotham and Kiron [6] talk about the case of Bridgestone in which insight generated through analytics allows for a completely novel way of engaging with customers and marketing products through proactive service calls. Similar radically new business models can also be seen in the investment management industry, where information from social media, corporate websites, news postings, and consumers' interactions can help investors identify companies that will be successful in the future, going beyond

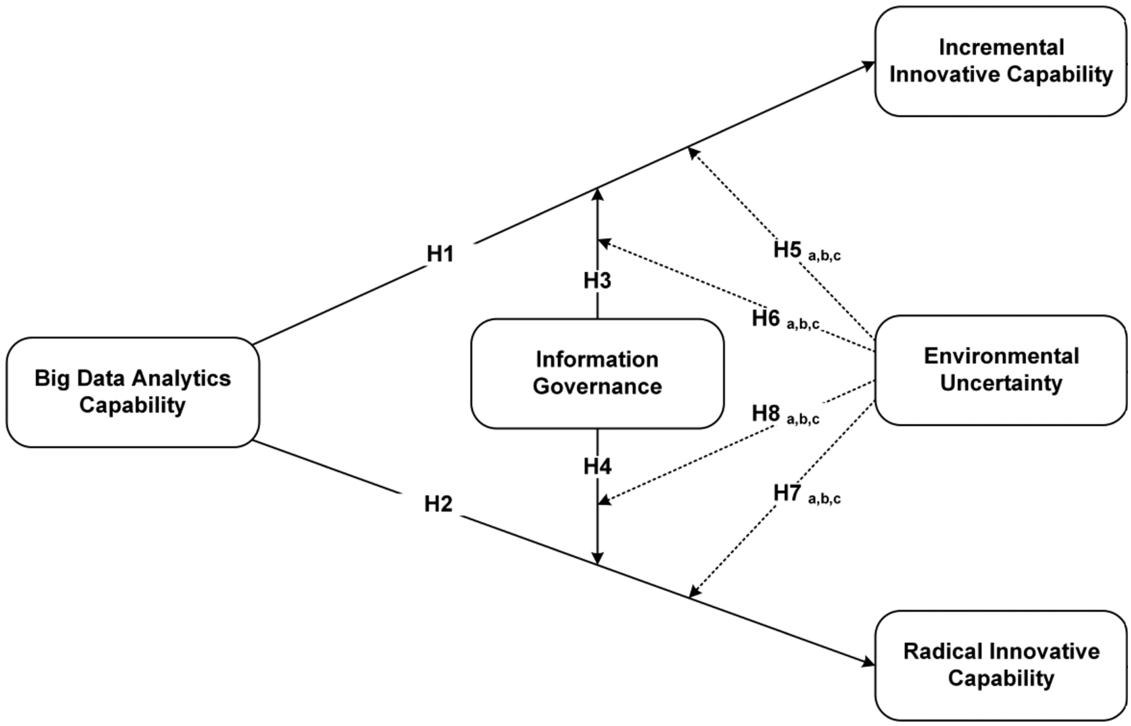

Fig. 1. Conceptual research model with hypothesized relationships.

those that are listed in the stock exchange. Based on the foregoing discussion, we hypothesize that:

H1. Big data analytics capabilities have a positive effect on incremental innovation capability

H2. Big data analytics capabilities have a positive effect on radical innovation capability

3.2. The moderating effect of information governance

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 [6]. Hence, establishing structural, procedural, and relational practices around big data are argued to amplify the effects of a firm's BDAC. 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?"* [49]. As such, information governance can be perceived as a framework to optimize the value that is generated from information within the firm. Being able to maximize the value from the information artifact, however, requires a set of complementary resources to transform data and the resulting insight into innovation capabilities. Therefore, information governance will only have positive effects if it is complemented with the presence of a strong BDAC. Specifically, to amplify the value derived from a BDAC, firms must pay close attention to the structural, procedural, and relational practices, that jointly constitute a firms information governance scheme [11].

Structural practices are important in achieving such outcomes as they are concerned with the systematic arrangement of people, departments, and other subsystems within the organization [66]. The structure of big data analytics teams within firm boundaries and the corresponding flow of data and information is a fundamental component. Some early research has noted that defining a clear structure and allocating appropriate decision rights schemes relating to data and information, are key success factors, especially in projects that extend tight departmental and functional boundaries [67]. O the other hand, procedural practices include both formal and informal mechanisms that help organizations reduce wasteful spending and optimize big data-related choices. Such practices include procedures such as determining what data will be gathered, stored, and analyzed, and even establishing the required skills of technical and business employees [11]. Procedural practices are central in amplifying the value that is produced from BDACs since they dictate how information governance is executed at different levels within the organization and at different inflection points of the information life cycle. Therefore, they determine the collective knowledge of the resources and their orchestration toward specific outcomes [68]. Last, relational practices dictate the roles and responsibilities of employees and determine how they should be adapted based on organizational demands [45]. I the contact of big data, relational practices are responsible for aligning individuals with the goals of strategy, thereby giving a BDAC a direction toward strategic objectives. Part of these practices include activities of building knowledge among the employees, which is a critical aspect of enhancing the outcomes of a BDAC.

Companies that are most innovative with analytics, according to recent reports, are more likely to have formulated a coherent governance plan for the information artifact [9]. Strong information governance practices facilitate data sharing, which in turn amplifies the effect on innovation outcomes [13]. According to a study by Deloitte two central obstacles for boards working with innovation include a lack of insight (47 %) and an organizational design which makes it hard to handle data-driven knowledge (46 %) [69]. This finding is also highlighted in recent empirical studies, where a large number of companies indicate that they cannot achieve the full potential of big data analytics projects due to the inability to access internal data because of unclear regulations, a lack of formal procedures of data handling from extraction to insight generation as well as organizational structures that do not facilitate data circulation ([70,47]). Yet, when firms combine structured adoption of big data analytics with well-defined information governance practices throughout the organization, this leads to positive returns and amplified effect of big data analytics on innovation outcomes [12]. As such, information governance exerts positive complementary effects when combined with a strong BDAC. A solid information governance needs to be more than a system of tactics to derive value, it should be capable of influencing organizational behavior and help strengthen the insight generated by a firm's BDAC [71]. This is because information governance dictates how data are shared, the quality of data and generated insights as well as the formal procedures of communicating outcomes with executives of all domains [72]. Simply sharing data and insight within and between organizations cannot work without having established an appropriate structure, processes, and well-defined roles [11]. Information governance enables data flows and promoted data-driven decision-making 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 [6]. From the above argument we hypothesize that:

H3. Information governance positively moderates the impact of big data analytics capabilities on incremental innovation capability

H4. Information governance positively moderates the impact of big data analytics capabilities on radical innovation capability

3.3. Conditioning effects of the external environment

The conditions under which BDACs add value have been a subject of much debate, and have been theoretically argued to be heavily contingent from all aspects of the external business environment [27]. In stable environments, where externals changes are infrequent and tend to be predictable and incremental, big data analytic capabilities are argued to result in incremental changes [64]. On the contrary, in unpredictable, fast-paced, and turbulent environments, existing modes of operating quickly erode, so BDACs are necessary to maintain competitiveness by driving radical innovation [73]. In this study, we differentiate environmental uncertainty conditions in terms of dynamism, heterogeneity, and hostility [74]. Dynamism is concerned with the unpredictability on the demand side, heterogeneity is defined as the uncertainty on the supply side, while hostility has to do with the variability regarding longer-term trends in the industry [75]. Although these external environmental conditions are rather distinct, they have been argued to have an impact on a firm's internal structuring in relation to its effect on BDACs and both types of innovation capabilities. As such, we examine the moderating effect that each separate dimension has on the previously stated hypotheses. In dynamic environments, it may be difficult to develop strong BDACs as the speed of change can render investments obsolete [76]. Under such conditions, the ability to orchestrate big data resources through information governance practices can help maintain strong BDACs and subsequently enhance incremental and radical innovation capabilities [77].

A solid information governance can help make rapid decisions regarding the allocation of resources, access data that are necessary in shorter times, and promote swifter responses toward innovation outcomes [78]. In conditions of environmental heterogeneity, a well-established information governance can provide seamless and consistent access to relevant customer, production, market, and operation-related data [79]. Firms deploying their BDACs in highly uncertain and hostile markets will benefit because, when competition is fierce, companies are coerced to develop radical innovations, explore new markets, and find new or revamped ways to compete and differentiate [80]. BDACs can be of increased relevance in such contexts because they facilitate the rapid identification of emerging opportunities through the generation of insight combining data from multiple sources [81]. In sum, our rationale suggests that information governance and effects of BDACs on innovation will be amplified under the described conditions of environmental uncertainty, dynamism, heterogeneity, and hostility. From the above argument we hypothesize that:

H5 – 6: Greater levels of environmental a) dynamism, b) heterogeneity, and c) hostility will amplify the positive effect of big data analytics capabilities on incremental and radical innovation capability

H7 – 8: Greater levels of environmental a) dynamism, b) heterogeneity, and c) hostility will amplify the positive moderating impact of information governance on the relationship between big data analytics capabilities and incremental and radical innovation capability

4. Methods

4.1. Data

To empirically test the research hypotheses, we developed a survey instrument and sent it out to key informants within firms. Before doing that, however, we conducted a small-cycle pre-test with 24 firms to determine the statistical properties of the items and constructs. Through the pretesting we were able to assess the content and face validity of items and to make sure that key respondents would be in place to comprehend they survey as intended. As part of the main study, we used a population of approximately 1500 firms from a mailing list of Chief Information Officers and IT managers that were working in Greece. Typically, employees in these positions are best equipped to answer questions regarding IT investments and overall IT strategy and performance. As in most cases they talk directly to senior management, they have also detailed information about the financial and competitive positioning of their organizations. To ensure a collective response, all respondents were asked to consult with other employees in their organization for information that was asked in the questionnaire that they were not knowledgeable about. Data collection lasted for roughly three months (April 2017 – July 2017), and the mean completion time of the survey was 14 min. In total, 193 respondents from different companies started the survey, and 175 provided complete responses that were used for further analysis Table 1.

Table 1
Sample Characteristics.

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%

As nonresponse bias is a common problem in large-scale survey studies, we took measures 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. All respondents were provided with an incentive to participate in the study and were given a personalized report which benchmarked their organizations performance in several areas to compared to the industry and country means [82]. Following the initial invitation to participate in the questionnaire, all of the respondents were re-contacted on three separate occasions to remind them to complete the survey with a two-week gap between them. After the data collection procedure was completed, and to make sure that the data did not contain any bias, we compared early and late responses on construct level to make sure that no significant differences existed [83]. We developed two groups of responses; 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 nonresponding 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 et al. [84]. *Ex-ante*, respondents were assured that all information they provided would remain completely anonymous and confidential, and that any analysis would be done solely on an aggregate level for research purposes. *Ex-post*, Harman's one factor test was employed, which indicated that a single construct could not account for the majority of variance [85].

4.2. Variable definition and measurement

BDAC is defined in accordance with the study of Gupta and George [1] 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 dimensions that together form a BDAC are big data-related tangible, human skills, and intangible resources, which in turn are developed as second-order formative constructs, comprising of seven first-order constructs.

Information Governance (IG) is defined according to the study of Tallon et al. [11] as a collection of capabilities or practices for the creation, capture, valuation, storage, usage, control, access, archival, and the deletion of information over its life cycle. In this definition it is clear that the two main objectives of information governance 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 [86] and building on related work on information governance [11], 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 an IG are formulated as first-order reflective constructs. Past studies were used to identify and operationalize each of the underlying dimensions ([11,46]). A pretest was also conducted with several experts through a small-cycle study to ensure the validity and reliability of corresponding items.

Innovative Capability (IC). An innovative capability 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 [87]. We operationalized the notion through two first-order latent constructs: *incremental innovative capability* (INC) and *radical innovative capability* (RAD). INC was quantified through three indicators assessing an organization's capability to reinforce and extend its existing expertise and product/service lines. Likewise, RAD was measured through three indicators that asked respondents to evaluate their organization's ability to make current product/service lines obsolete [52].

Environmental Uncertainty. To examine the degree of environmental uncertainty we utilized three constructs: dynamism, heterogeneity, and hostility [74]. Dynamism is defined as the rate and unpredictability of environmental change. Heterogeneity reflects the complexity and diversity of external factors, such as the variety of customer buying habits and the nature of competition. Hostility is defined as the availability of key resources and the level of competition in the external environment.

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 modelling technique. Specifically, the software package SmartPLS 3 was used to conduct all analyses [88]. PLS-SEM is considered as an appropriate methodology for this study because it permits the simultaneous estimation of multiple causal relationships between one or more independent variables and one or more dependent variables [89].

5.1. Measurement model

As the model contains reflective and formative constructs, we used different assessment criteria to evaluate each. First-order reflective latent constructs were assessed by examining their reliability, convergent validity, and discriminant validity. Reliability was gauged at both the construct and item level. We first looked at the construct level and examined Composite Reliability, and Cronbach Alpha values, and established that their values were above the threshold of 0.70 [90]. At a second stage, indicator reliability was examined by determining if construct-to-item loadings were above the threshold of 0.70. To determine 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. We tested for discriminant validity through three ways. First, we looked at each constructs AVE square root to establish that it is greater than its highest correlation with any other construct (Fornell-Larcker criterion). Second, we examined if each indicators' outer loading was greater that its cross-loadings with other constructs (Farrell, 2010). Third, we looked at Heterotrait-Monotrait ratio (HTMT) and ensured that all values are below 0.85, which is an indication of sufficient discriminant validity. The results we obtained from the analysis confirm that there is sufficient discriminant validity (Appendix B). 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 [91].

To examine the validity of formative indicators, we first looked at the weights and significance levels with their respective constructs. In 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 et al. [92] and Schmiedel et al. [93] guidelines using Edwards [94] adequacy coefficient (R_a^2). To do this, we summed the squared correlations between formative items and their respective formative construct and then divided the sum by the number of indicators. All of the constructs' R_a^2 values exceeded the lower threshold of 0.50 (Table 3), which indicates that the majority of variance in the items is shared with the overarching construct and that the indicators are valid representations of the construct. In a similar manner, for the higher-order constructs, we started by examining the weights of the formative lower-order constructs on their higher-order constructs (five second-order constructs and one third-order construct). The outcomes indicated that the weights for all constructs were significant and the results of Edward adequacy coefficient for each was found to be larger than the limit of 0.50 [94]. In sequence, we assessed 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 cutoff of 3.3 is used for formative constructs [95]. The values of all first-order, second-order, and third-order constructs were found to be below the limit of 3.3 which is indication of an absence of multicollinearity.

5.2. Structural model

Inn Fig. 2 the summarized structural model for the PLS analysis is depicted, in which the explained variance of endogenous variables (R^2)

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(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**			
(13) Dynamism	0.30	0.32	0.25	0.23	0.32	0.25	0.36	0.21	0.27	0.28	0.31	0.37	**0.87**		
(14) Heterogeneity	0.25	0.43	0.31	0.27	0.45	0.43	0.33	0.31	0.28	0.17	0.37	0.27	0.37	**0.81**	
(15) Hostility	0.21	0.44	0.40	0.35	0.35	0.48	0.20	0.32	0.25	0.19	0.31	0.25	0.35	0.28	**0.81**
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	4.67	4.13	4.79
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	1.45	1.34	1.64
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	0.87	0.86	0.89
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	0.91	0.90	0.86
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	0.92	0.91	0.89

Table 3
Higher-order construct validation.

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	

and the standardized path coefficients (*β)* are presented. In contrast 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 the 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 extracted by running a bootstrap analysis with 5000 resamples. As is presented in Fig. 2, we find empirical support for bot direct hypotheses. We find that a firms' BDAC has a positive and significant impact on both INC (H1 $\beta = 0.451$, t = 7.132, and $p < 0.001$) and RAD (H2 $\beta = 0.426$, t = 6.436, and $p < 0.001$). When examining the moderating impact of information governance, we find a positive and significant influence in relation to RAD (H4 $\beta = 0.192$, t = 2.211, $p < 0.05$); nevertheless, with regard to a firm's INC the effect is found to be non-significant (H3 $\beta = 0.089$, t = 0.865, and $p > 0.05$). Overall, the structural model explains 41.1 % of variance for INC ($R^2 = 0.411$) and 40.2 % for RADs ($R^2 = 0.402$). These coefficients of determination represent moderate to substantial predictive power [96].

5.2.1. *Prediction analysis*

In addition to examining the R^2 and f^2 respectively, the model was assessed by examining the the Q^2 predictive relevance of exogenous and the effect size q^2 [97]. This indicator measures how well-observed values are reproduced by the model and its parameter estimates, verifying as such the model's predictive validity through sample reuse [98]. The technique is a synthesis of cross-validation and function fitting and examines each construct's predictive relevance by omitting selected inner model relationships and computing changes in the criterion estimates (q^2) [96]. Values of the Q^2 predictive relevance that are greater than 0 imply that the structural model has predictive relevance, whereas values below 0 are an indication of insufficient predictive relevance [96]. We find that both INC ($Q^2 = 0.318$), and RAD ($Q^2 = 0.309$) have satisfactory predictive relevance [96]. In addition, q^2 value range from moderate to high reveals (above 0.15 and 0.35, respectively) an adequate effect size of predictive relevance.

To examine model fit, a test of composite-based Standardized Root Mean Square Residual (SRMR) was performed. The SRMR value is obtained through the difference between the observed correlation and the model implied correlation matrix. The current SRMR yields a value of 0.061, which is below the threshold of 0.08, thus confirming the overall fit of the PLS path model [99]. In order to establish the predictive validity of the model, we performed a cross-validation analysis with holdout samples [100]. Based on the guidelines of Carrión et al. [101], our sample is randomly divided into a training sample (n = 115) and a holdout sample (n = 60). We use the training sample to calculate the path weights and coefficients. In sequence, the holdout sample observations are normalized and construct scores are created using the training sample estimations. The following step is to normalize the construct scores of the holdout sample and then use them to create prediction scores. The outcomes of this test ensure the predictive validity of the model, since the R^2 for the holdout sample for INCs ($R^2 = 0.522$) and that of RADs ($R^2 = 0.431$) is almost the same as to that of the training sample for each, respectively ($R^2 = 0.513$ and $R^2 = 0.447$). Even though model fit assessment criteria are not a prerequisite, researchers have called for the development of evaluation criteria that can better support the prediction-oriented nature of PLS-SEM [102].

5.2.2. *Unobserved heterogeneity and subgroup analysis*

To test Hypotheses 5–8, we employ the finite mixture partial least squares (FIMIX-PLS) algorithm [103]. The FIMIX-PLS algorithm can

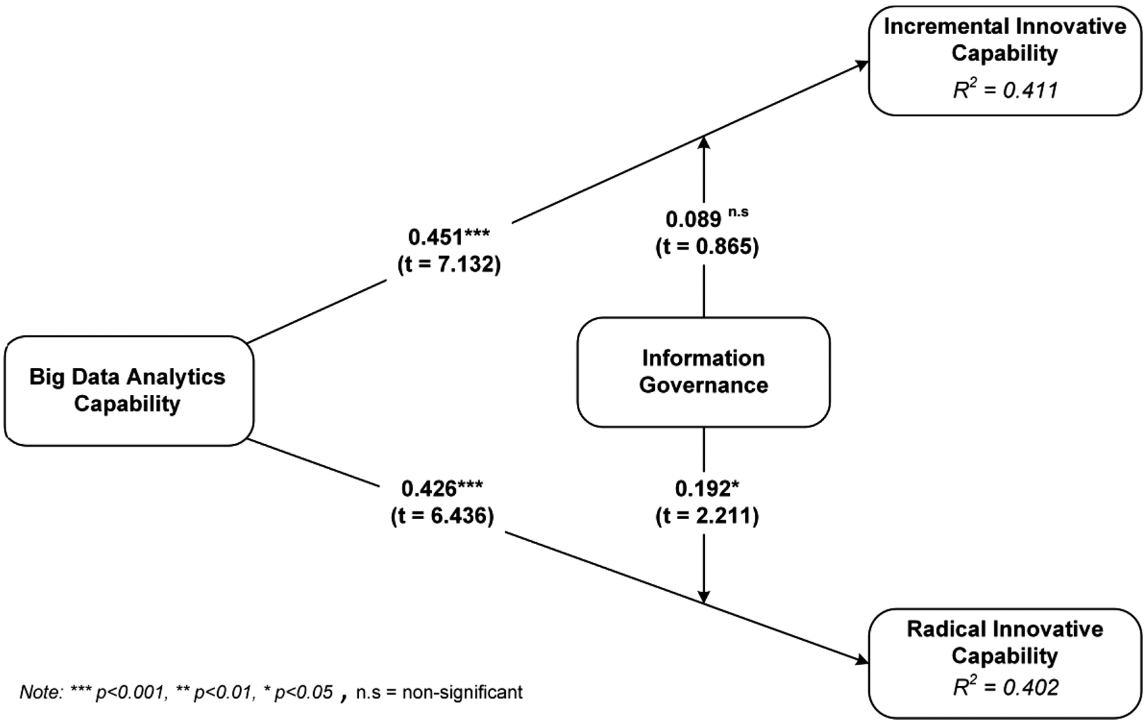

Fig. 2. Estimated causal relationships of structural model.

detect whether there are factors that are not included in our analysis, which might explain differences across various groups of firms. An a priori subgroup analysis might not provide the most appropriate segmentation method because of heterogeneity being unobservable, making it difficult to separate observations into subpopulations (i.e., the process of creating subgroups by prespecifying subgroup sizes might not distinguish suitably different levels of uncertainty within an environment). While observable characteristics are often inadequate in capturing heterogeneity in data, ignoring heterogeneity can lead to biased parameter estimates and potentially flawed conclusions [104]. Hence, we apply FIMIX-PLS, which can provide more fine-grained results, while accounting for unobserved heterogeneity. For segmentation tasks in the PLS context, FIMIX-PLS represents the primary choice, because as a response-based segmentation approach, it facilitates the effective identification of subgroups and can classify data of the inner path models estimates on the basis of heterogeneity [103]. As such, FIMIX-PLS combines the advantages of PLS path modeling with the strengths of classifying groups by finite mixture models.

We follow the unobserved heterogeneity detection method to define segments as proposed by Becker et al. [105]. We start by applying the FIMIX-PLS algorithm to narrow the range of statistically well-fitting segments. The FIMIX-PLS algorithm was executed 10 times for g = 2–5 segments, using the Akaike Information Criterion (AIC), Modified AIC with Factor 3 (AIC3), Bayesian Information Criterion (BIC), Consistent AIC (CAIC), Hannan-Quinn Criterion (HQ), and the normed Entropy Statistic (EN) as indicators to identify the appropriate segmentation solution [106]. According to Sarstedt et al. [106], the appropriate number of segments depends on a joint evaluation of the CAIC and AIC_3 indicators. These indicators, as presented in Table 4, indicate that the two-segment solution is the most appropriate. In addition, we did not take into account solutions with more than three segments, because segment sizes become increasingly fragmented (smallest subgroup size attains levels of less than 2 %), which are likely to be irrelevant to theory and practice. These small subgroups are relatively less important for deriving managerial implications and are presumably caused by outliers. In the two-subgroup solution, each case exhibits a probability of membership in either subgroup, resulting in a larger group with $\pi_1 = 0.54$ and a smaller one with $\pi_2 = 0.46$.

Next, we assigned each case to either subgroup 1 or subgroup 2, according to its probability of group membership and analyzed both subgroups by applying the multi-group analysis partial least square (MGA-PLS) algorithm. We do so to identify that its segments are differentiable by assessing the measurement invariance/equivalence and the significance of differences in path coefficients between segments. For both subgroups, measurement model criteria were established as in the global model. The results of the multi-group analysis and the significance of the differences between the two subgroup paths and coefficients of determination are reported in Table 5. In subgroup 1, the impact of BDACs on INC ($\beta = 0.593$, $t = 22.712$, and $p < 0.001$) and RAD ($\beta = 0.582$, $t = 24.106$, and $p < 0.001$) were considerably greater than that for subgroup 2, respectively ($\beta = 0.293$, $t = 4.126$, $p < 0.001$ and $\beta = 0.312$ $t = 5.174$ $p < 0.001$). Concerning the moderating effect of information governance on the relationship of BDACs on incremental innovative, subgroup 1 demonstrated a greater effect ($\beta = 0.182$, $t = 2.692$, and $p < 0.01$) as compared to subgroup 2 ($\beta = 0.049$, $t = 0.542$, and $p > 0.05$). Similar findings were noted on the relationship with radical innovation capabilities, where subgroup 1 ($\beta = 0.262$, $t = 2.995$, and $p < 0.001$) exerted stronger effects than subgroup 2 ($\beta = 0.093$, $t = 1.254$, and $p > 0.05$).

The two subgroup solutions resulting from FIMIX-PLS provided a better fit than the global model, particularly for explaining a firm's incremental and radical innovation capabilities. The final step of the unobserved heterogeneity detection method is to turn unobserved heterogeneity into observed heterogeneity by making segments accessible [105]. We used multiple statistical techniques to assess the theoretical meaning of the segments in relation to environmental uncertainty variables. First, we tested a binary logistic regression model using the membership values (1 – subgroup 1, 0 – subgroup 2) as the dependent variable, and dynamism, heterogeneity, and hostility as the independent variables. The results demonstrate that the subgroups can be separated meaningfully on the basis of environmental dynamism ($p < 0.001$), because the other environmental factors are found to be nonsignificant, and the classification corresponded to 69.1 % of the FIMIX-PLS segregation. The Hosmer and Lemeshow test further

Table 4
FIMIX-PLS evaluation criteria.

S	AIC	AIC_3	BIC	CAIC	HQ	EN	Relative segment sizes Π_G				
							$g = 1$	$g = 2$	$g = 3$	$g = 4$	$g = 5$
$s = 2$	2484.93	2561.06	2740.93	2755.93	2673.67	0.519	0.54	0.46			
$s = 3$	2673.32	2727.2	2916.07	2957.07	2731.83	0.624	0.58	0.32	0.10		
$s = 4$	2558.48	2623.48	2763.09	2834.09	2629.39	0.673	0.61	0.20	0.10	0.09	
$s = 5$	2524.02	2588.02	2736.51	2800.51	2621.42	0.792	0.61	0.17	0.13	0.09	0.02

AIC: Akaike Information Criterion; AIC_3: Modified AIC with Factor 3; BIC: Bayesian Information Criterion; CAIC: Consistent AIC; HQ: Hannan-Quinn Criterion; and EN: Entropy Statistic.

confirmed our model. Finally, the Wald criterion suggested that only environmental dynamism contributed significantly to accurate FIMIX-PLS segment allocations ($p = 0.01$) because dynamism and hostility were not significant predictors. To validate these results, we also performed a discriminant analysis in which both groups are found to have equal variance (Box's M = 12.17 $p > 0.01$), and environmental dynamism ($p < 0.05$) is noted as the only significant contributor to the FIMIX classification. Furthermore, standardized canonical discriminant function coefficients and structure matrix indicate dynamism as the highest predictor of group membership.

6. Discussion

Despite the hype around big data continuously growing, the mechanisms and conditions through which innovation can be enhanced still remain an underexplored 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 information governance theory, we examine the complementary effects 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. Our results provide some interesting theoretical and practical implications which are discussed below, but also present some limitations, which we highlight in the concluding subsection.

6.1. Theoretical implications

From a theoretical point of view, our study adds to existing knowledge in several ways. First, we examine if a big data analytics capability can help develop two important, but distinct, types of innovative capabilities, radical and incremental. By doing so, 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. Although there have been some research studies linking the adoption of big data analytics with innovation-related outcomes (Lehrer, et al., 2018), this is one of the first large-scale empirical studies that documents a positive and significant link with two distinct types of innovation capabilities. It is also one of the first studies to document how an RBV conceptualization of a big data analytics capability can lead to enhancements of innovation capabilities.

Second, we add to the existing body of knowledge by examining the underexplored role of information governance in mobilizing and leveraging the information artifact. Our results show that while information governance may not have any substantial influence in amplifying insight toward 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. In fact, how organizations are structured and the effect that this has on information and knowledge flows is well-documented in management literature [107]. What is new in the era of big data though is that data and information are the input of a more technologically based process, where incomplete information or inability to access or use some information resources may significantly hinder the outcomes that can be delivered. In the case of big data analytics, without the presence of a structured information governance plan, outcomes indicate that investments will have a more limited effect on outcomes.

Third, we also find support that under conditions of high environmental dynamism, effects of information governance and BDACs are significantly amplified. These results demonstrate that in industries that are characterized by fast-paced changes and fierce competition, establishing information governance practices is fundamental for competitive success. This is one of the first studies to document such outcomes and provides support for the argument that investing in big data analytics technologies and opting for data-driven decision-making is of heightened importance when there is competitive pressure to do so and a strong requirement for achieving an edge over rivals. As the market becomes increasingly fast-paced and there is limited time and information to base decisions on, big data analytics may provide the distinct edge over competitors in delivering insight that can help drive both improvements in existing products and services as well as critical insight toward radically new ones. In fact, practice-based reports document increasingly more companies basing completely new business models on data-driven strategies and many that utilize such methods for providing incremental improvements to their existing ones. While the approaches that are used and the industries to which they are applied may vary significantly, they all require a similar set of resources to drive a BDAC, and the same underlying dimensions of information governance practices to leverage and mobilize the information artifact. The results of our study indicate that by developing these two pillars, organizations will be able to strengthen their innovation capabilities and increasingly more so in conditions of heightened dynamism.

6.2. Practical implications

This study also highlights some important practical implications. Because our conception of BDACs goes beyond technical resources but

Table 5
Global model and MGA-PLS results for two subgroups.

	Global	FIMIX				
		S_1 High environmental dynamism (n = 115)	S_2 Low environmental dynamisms (n = 60)	Path Coefficients Diff. (S_1-S_2)	Welch-Satterthwait Test Diff.	Parametric Test Diff.
BDAC → Incremental Innovative Capability	0.451***	0.593**	0.293***	0.300	Sig.***	Sig.***
BDAC → Radical Innovative Capability	0.426***	0.582***	0.312***	0.270	Sig.***	Sig.***
Information governance x BDAC → Incremental Innovative Capability	0.089	0.182**	0.049	0.133	Sig.***	Sig.***
Information governance x BDAC → Radical Innovative Capability	0.192*	0.262**	0.093	0.169	Sig. **	Sig. **
R^2 (Incremental Innovative Capability)	0.411	0.527	0.293	0.234	Sig.***	Sig.***
R^2 (Radical Innovative Capability)	0.402	0.551	0.270	0.281	Sig.***	Sig.***

Diff. = Significance of the path difference for the multi-group analysis
*** $p < 0.001$, ** $p < 0.01$, and * $p < 0.05$

also human skills and intangible ones, we document the importance of placing an equal amount of emphasis on the broader picture within the organization when it comes to big data. It is a rather common conception in organizations to see big data as a solely technical activity, which includes the administration of databases, data collection and curating, and applying sophisticated analytic algorithms and techniques. Although this is in part true, it is also important for managers to recognize that the main challenge in extracting value from their investments does not have to do so much with the technical issues but rather, in embedding these technologies into the organizational fabric and leveraging them for strategic outcomes. Doing so requires investments in resources that are not purely technical, such as human skills and establishing a data-driven culture and continuous learning. It is by adopting a holistic perspective of the organization when taking into account big data analytics deployments that firms can realize performance gains. In fact, many practice-based reports and empirical studies showcase that the biggest barriers firms face when trying to generate value from big data analytics concern aspects of the broader organization instead of purely data and technical-related elements [9].

Furthermore, our findings highlight the importance of information governance, which is a very understudied aspect when it comes to big data analytics and business value. 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 [108]. 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 [15]. The significance of information governance is particularly relevant in deriving value out of any investments because it facilitates the necessary flow of information throughout the organization. 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 toward deriving radical innovation capabilities is amplified. This has great significance for higher-level executives because radical innovations have the potential to generate competitive success if exploited swiftly. It also indicates that top management should be responsible for developing and enforcing information governance practices jointly with other unit managers, as it is often the case that IT managers are restricted in their access on other units information, and often do not have the decisional power to enforce such practices throughout the organization [109]. This is particularly relevant in the case of large companies or ones that are highly decentralized.

6.3. 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. Since the data used in this study were based on respondents' perceptions, and since we based collection on a single key informant, there is a possibility of bias. This effectively means 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 interrater validity and to improve internal validity. Second, although we examine the value of BDACs on a firm's innovative capabilities, we do not factor in the influence of the internal environment. It is highly likely that the value of directing big data initiatives may be more or less beneficial in different conditions [110,111]. 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. Finally, the sampling of companies was conducted in Greece, which could limit the generalizability of results to a certain extent. As Greece has been under conditions of economic recession for almost a decade now, investments in big data analytics may be at lower levels as compared to other stronger global economies. Nevertheless, many countries worldwide are in similar economic environments, therefore providing generalizability to the results beyond a single country.

CRediT authorship contribution statement

Patrick Mikalef: Conceptualization, Methodology, Software, Writing - original draft, Writing - review & editing. **Maria Boura:** Writing - original draft. **George Lekakos:** Writing - original draft. **John Krogstie:** Writing - original draft, Supervision.

Acknowledgement

This research has been partially funded by the Research Center of the Athens University of Economics and Business.

Appendix A. Survey Instrument

Measure	Item	References
Information Governance		Developed based on Tallon et al. [11]
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.	
	STR2. use steering committees to oversee and assess data values and costs	
Procedural Practices	In our organization, we have controlled practices regarding data management in terms of _____________	
	PCR1. setting retention policies (e.g., time to live) of data	
	PCR2. backup routines	
	PCR3. establishing/monitoring access (e.g., user access) to data	
	PCR4. classifying data according to value	
	PCR5. monitoring costs versus value of data	
Relational Practices	In our organization, we _____________	
	RLT1. educate users and non-IT managers regarding storage utilization and costs	
	RLT2. develop communications regarding policy effectiveness and user needs	
Big Data Analytics Capability		Adopted from Gupta and George [1]
Tangible		
Data	D1. We have access to very large, unstructured, or fast-moving data for analysis	
	D2. We integrate data from multiple sources into a data warehouse for easy access	
	D3. We integrate external data with internal to facilitate analysis of business environment	
Basic Resources	BR1. Our 'big data analytics' projects are adequately funded	
	BR2. Our 'big data analytics' projects are given enough time to achieve their objectives	
Technology	T1. We have explored or adopted parallel computing approaches (e.g., Hadoop) to big data processing	
	T2. We have explored or adopted different data visualization tools	
	T3. We have explored or adopted new forms of databases such as Not Only SQL (NoSQL)	
	T4. We have explored or adopted cloud-based services for processing data and performing analytics	
	T5. We have explored or adopted open-source software for big data analytics	
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.	
	MS2. Our DBA managers are able to coordinate big data-related activities in ways that support other functional managers, suppliers, and customers	
	MS3. Our BDA managers are able to understand and evaluate the output extracted from big data	
	MS4. Our BDA managers are able to understand where to apple big data	
Technical Skills	TS1. Our 'big data analytics' staff have the right skills to accomplish their jobs successfully	
	TS2. Our 'big data analytics' staff are well trained	
	TS3. We provide big data analytics training to our own employees	
	TS4. Our 'big data analytics' staff have suitable education to fulfill their jobs	
Intangible		
Data-driven Culture	DD1. We base our decisions on data rather than on instinct	
	DD2. We are willing to override our own intuition when data contradict our viewpoints	
	DD3. We continuously coach our employees to make decisions based on data	
Organizational Learning	OL1. We are able to acquire new and relevant knowledge	
	OL2. We have made concerted efforts for the exploitation of existing competencies and exploration of new knowledge	
	OL3. We are able to assimilate relevant knowledge	
	OL4. We are able to apply relevant knowledge	
Innovative Capability	How would you rate your organizations capability to generate the following types of innovations in the products/services you introduce	Adopted from Subramaniam and Youndt [52]
Incremental	INC1. Innovations that reinforce our prevailing product/service lines	
	INC2. Innovations that reinforce our existing expertise in prevailing products/services	
	INC3. Innovations that reinforce how you currently compete	
Radical	RAD1. Innovations that make our prevailing product/service lines obsolete	
	RAD2. Innovations that fundamentally change our prevailing products/services	
	RAD3. Innovations that make our expertise in prevailing products/services obsolete	
Environmental Uncertainty		Adopted from Newkirk and Lederer [74]
Dynamism	With respect to the uncertainty of your environment, please indicate how much you agree or disagree with the following statements	
	DYN1. Products and services in our industry become obsolete very quickly	
	DYN2. The product/services technologies in our industry change very quickly	
	DYN3. We can predict what our competitors are going to do next (Reverse coded)	
	DYN4. We can predict when our products/services demand changes (Reverse coded)	
Heterogeneity	With respect to the uncertainty of your environment, please indicate how much you agree or disagree with the following statements	
	HET1. Customer buying habits	
	HET2. Nature of competition	
	HET3. Product lines	
Hostility	With respect to the uncertainty of your environment, please indicate how much you agree or disagree with the following statements	
	HOS1. Scarce supply of labor	
	HOS2. Scarce supply of materials	
	HOS3. Tough price competition	
	HOS4. Tough competition in product/service quality	
	HOS5. Tough competition in product/service differentiation	

Appendix B. Heterotrait-Monotrait Ratio (HMTM)

	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(4) Managerial Skills												
(5) Technical Skills	0.548											
(6) Data-driven Culture	0.342	0.519										
(7) Organizational Learning	0.425	0.449	0.319									
(8) Structural Governance	0.353	0.273	0.287	0.268								
(9) Procedural Governance	0.396	0.346	0.290	0.395	0.374							
(10) Relational Governance	0.370	0.349	0.382	0.368	0.388	0.482						
(11) Incremental Innovation	0.295	0.285	0.272	0.312	0.472	0.362	0.372					
(12) Radical Innovation	0.421	0.332	0.273	0.314	0.353	0.422	0.394	0.243				
(13) Dynamism	0.253	0.347	0.412	0.365	0.375	0.357	0.360	0.411	0.408			
(14) Heterogeneity	0.278	0.532	0.432	0.349	0.324	0.366	0.294	0.512	0.337	0.293		
(15) Hostility	0.341	0.346	0.462	0.247	0.363	0.226	0.443	0.378	0.521	0.291	0.335	

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