Big Data Analytics as an Enabler of Process Innovation Capabilities: A Configurational Approach

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Abstract. A central question for information systems (IS) researchers and practitioners is if, and how, big data can help attain a competitive advantage. Anecdotal claims suggest that big data can enhance a firm's incremental and radical process innovation capabilities; yet, there is a lack of theoretically grounded empirical research to support such assertions. To address this question, this study builds on the Resource-Based View and examines the fit between big data analytics resources and organizational contextual factors in driving a firm's process innovation capabilities. Survey data from 202 chief information officers and IT managers working in Norwegian firms is analyzed by means of fuzzy set qualitative comparative analysis (fsQCA). Results demonstrate that under different patterns of contextual factors the significance of big data analytics resources varies, with specific combinations leading to high levels of incremental and radical process innovation capabilities. These findings suggest that IS researchers and practitioners should look beyond direct effects, and rather, identify key combinations of factors that lead to enhanced process innovation capabilities.

Keywords: Big data analytics, process innovation capabilities, fsQCA, resource-based view, contingency theory

1 Introduction

The domain of big data analytics has received increasing attention from academics and business practitioners over the past few years. By analyzing large volumes of unstructured data from multiple sources, actionable insights can be generated that help firms transform their business and gain an edge over their competition [1]. Such insights are particularly relevant, especially in dynamic and high-paced business environments, in which the need to continuously innovate is enhanced [2]. Quickly recognizing the potential of big data analytics, organizations have targeted their initiatives towards improving the efficiency and quality of their processes. Nevertheless, effective use of big data analytics within organizations, is argued not only to help create incremental improvements to existing processes, but also to lead to help develop exploration or radical process innovation capabilities [3]. As a result, the successful application of big data analytics towards both incremental and radical process innovation capabilities can help organizations redefine their business and outperform their competitors [4]. The competence to successfully pursue process innovation represents an important capability, particularly for organizations that are exposed to a dynamic business environment. Despite this, organizations today are still facing challenges concerning the firm-wide deployment of big data analytics initiatives, and a difficulty to align their new investments towards the attainment of strategic goals [5].

Recognizing this issues that many companies face, several research commentaries have been written emphasizing the importance of delving into the whole spectrum of aspects that surround big data analytics [6, 7]. Nevertheless, empirical studies on the topic is are still quite limited, particularly in explaining how specific organizational goals should be achieved, and what factors influence their attainment [8]. Past literature reviews on the broader IS domain have demonstrated that there are multiple factors that should be taken into account when examining the value of IT investments [9], and especially in relation to process management and innovation [10-12]. 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 [13]. The main idea underlying the concept is that when firms manage to obtain valuable bundles of resources, they will develop the capacity to effectively utilize them towards strategic objectives [14]. 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 [15].

Building on these gaps, we seek to explore the importance that different combinations of big data analytics capability resources have on enhancing a firm's process innovation capabilities. While external requirements have always prompted change and innovation, new technologies of the digital age represent a key source of numerous affordances for process innovations today [16]. In fact, fundamental business transformations are often a result of integrating IT into business processes. The big data age offers manifold opportunities to promote process innovation, but to do so first requires identifying the value-creating resources [16]. In doing so, we differentiate between incremental and radical process innovation capabilities [4, 17], since the types of goals they are targeted towards will likely influence the importance of different combinations of resources [12]. In addition, we include contextual factors in our examination pertinent to the internal and external environment of the firm. Building on a sample of 202 survey responses from IT managers in Norwegian firms, we employ a configurational theory approach and examine the patterns of elements that lead to high levels incremental and radical process innovation capabilities. We do so through the novel methodological tool fsQCA, which allows the examination of such complex phenomena and the reduction of solutions to a core set of elements.

In section 2 we provide an overview of literature on big data analytics capabilities, process innovation capabilities, and some of the most important contextual factors when examining process innovation practices. In section 3, we introduce the logic of configurational theories, and develop a set of propositions that guide this research. Section 4 defines the methodology of the study, including the data, measurements, and reliability and validity tests, while in section 5 we present the results of the fsQCA analyses. In closing, we draw on the theoretical and practical implications of this study.

2 Background

2.1 Big Data Analytics Capabilities

A lot has been written on the relationship between different IT investments and business process management (BPM) projects [18]. The general consensus in the academic and research community is that IT acts as the enabler and the facilitator of changes identified in BPM projects [10]. Specifically, Sambamurthy, Bharadwaj and Grover [19] suggest that IT could be driving the modularization and atomization of business processes and enabling their combination and recombination to create new business processes. Recent articles have begun to develop this idea on a more theoretically grounded basis, both in relation to how the value of IT investments should be measured [10], as well as on how the context shapes this relationship [12]. It is generally accepted that while a strong IT capability may be more appropriate in assessing effects on business process management, the value of some resources that comprise it may be of a greater or lesser importance depending on the context of examination [12]. Despite the extended work the impact of IT capabilities on business process management and innovation [19, 20], empirical studies examining the enabling role of big data analytics are still scarce.

Past research has shown that when assessing the business value of IT investments, it is critical to take a broader view and capture all the underlying factors that enable effective and efficient use of IT as a differentiator of firm success [13]. Studies that examine the effects of a firms IT capability, typically base their theoretical assumptions and operationalization on the Resource-Based View (RBV) of the firm [21], which argues that a competitive advantage emerges from unique combinations of resources that are economically valuable, scarce, and difficult to imitate. Likewise, the main premise on which the notion of IT capability is built, is that while resources can be easily replicated, distinctive firm-specific capabilities cannot be readily assembled through markets, and can thus, constitute a source of a sustained competitive advantage [22]. Since the aim of this study is to define the main resources have an impact on process innovation capabilities, the choice of the RBV as the underlying theoretical framework is deemed as suitable. Consequently, we define big data analytics capability as the ability of the firm to capture and analyze data towards the generation of actionable insights, by effectively deploying its data, technology, and talent through firm-wide processes, roles and structures.

Building on prior studies of the RBV and on IT capabilities literature, we identify between three broad types of resources, tangible (e.g. physical and financial resources), human skills (e.g. employees skills and knowledge), and intangible (e.g. organizational culture and organizational learning) [23]. Regarding tangible resources, data, technology and other basic resources are considered critical for success. Despite the defining characteristics of big data being its volume, variety, and velocity, a common concern amongst IT strategists and data analysts are the quality and availability of the data they analyze [24]. It is also critical for firms to possess the necessary infrastructure for storing, sharing, and analyzing data, as well as analytics methods to turn data into insight [7]. Finally, basic resources such as financial support are necessary at all stages of big data projects, particularly when considering the long lag effects they have in producing measurable business value [15]. When it comes to human skills, literature recognizes that both technical and managerial-oriented skills are necessary to derive value from big data investments [25]. Specifically, regarding technical skills, Davenport and Patil [26] emphasize on the importance that the emerging job of the data scientist will have in the next few years throughout a number of industries. Yet, while technical skills are important, one of the most critical aspects of data science is the ability of data-analytic thinking and strategic planning based on data-driven insight [2]. In relation to intangible resources, a data-driven culture and organizational learning are widely regarded as important components of effective deployment of big data initiatives [8]. For firms that have deployed big data projects, a data-driven culture has been suggested to be a key factor in determining overall success and alignment with organizational strategy [27]. Yet, a complementary facet of governance is organizational learning, primarily due to the constantly changing landscape in terms of technologies and business practices, which require firms to infuse the idea of continuous learning into their fabric [28].

2.2 Process Innovation Capabilities

While BPM has traditionally emphasized on promoting incremental improvements through efficiency and effectiveness on business processes through standardization, automation, and optimization, there is also a stream of research that highlights the potential for radical process innovations [29, 30]. In today’s dynamic globalized business arena, process innovation is important for at least two reasons. First, process innovation is closely associated with product innovation [31]. Developing new products often requires changes in either existing processes, or even forming new ones when they involve techniques that are novel to the firm. In their empirical investigation, Fritsch and Meschede [32] show that process innovation has a positive effect on product innovation, and that by fostering process innovation, a firm will be able to improve its product quality or even to produce entirely new products. Second, the value of process innovation is proportional to the level of output produced by a given firm. Hence, as industries mature and increase their numbers and frequencies of use of their business processes, they have increased incentives to pursue process innovation [31].

In this study we examine a firm’s process innovation capability, which is defined as a firm's ability, relative to its competitors, to apply the collective knowledge, skills, and resources to innovation activities relating to new processes, in order to create added value for the firm [33]. We identify two main types of process innovation capabilities, incremental and radical [34]. An incremental process innovation capability is defined as an organizations ability to reinforce and extend its existing expertise in processes, by significantly enhancing or upgrading them [35]. On the other hand, a radical process innovation capability is focused around the ability of the firm to make current/existing processes obsolete through the introduction of novel ones [36]. Literature on BPM has focused quite heavily on methods for product business process innovation, yet, there is considerable skepticism on whether maturity models such the Capability Maturity Model (CMM) are able to capture the need for business process innovation [37]. Rather, the elements underpinning BPM and process innovation, emphasize on the importance of taking into account a holistic view, including the culture, IT, and people [38].

2.3 Contextual Factors

While the role of context has been researched extensively in the fields of information systems and organizational studies, it is still at a very early stage in the field of BPM [12]. While not explicitly the focus of many studies, contradicting findings pinpoint the contextuality of results [39], placing the context of examination as an important aspect that should be considered when looking at process management and particularly process innovation outcomes. Building on this, the principle of context awareness has been identified as a key perspective for successful BPM implementations [39]. This perspective is rooted in contingency theory [40],which assumes that there is not one universal best way to manage business processes, but rather, that management practices and resources should fit the organization and the external environment [12]. Similar views on process innovation have been found to be true on studies that adopt an strategic management and organizational research perspective [41].

A first contextual factor that is examined in this study is the goal of the organization, since goals directly influence the business process management practices and resources that are most suitable [12]. Several authors make the distinctions between exploitation and exploration, or else incremental and radical process innovation capabilities [42, 43]. Since the process of developing either incremental or radical innovations differs fundamentally, managers need to select and adapt their approach depending on the goal, thereby constituting the focus as an important contextual factor. Another important group of contextual factors have to do with the external environment of the organization. Particularly, the uncertainty of the environment is critical to consider since under such conditions organizations need to reconfigure the way the operate and emphasize more on analytical and research capabilities. Finally, an important group of contextual factors relate to the organization itself. Based on contingency theory, the size of the organization plays an important role since, typically, larger organizations require more formalized processes that cross vertical and horizontal functions than smaller firms [12]. Finally, type of industry is considered to be an important contextual factor, since practices and resources that may be effective in one industry may not be the most suitable in another [11].

3 Research Approach

Following the studies described above, research has begun to examine how these contextual factors coalesce in order to produce both types of process innovation outcomes for firms, incremental and radical [44]. Particularly in relation to the emerging area of big data analytics, little is known about what are the core resources that help drive a firm’s process innovation capabilities, and even less regarding the role of internal and external factors in shaping these requirements [25, 45]. While it may be useful to consider separate elements of context and examine their influence on outcomes of business process innovation, it is also important to research their combinations to derive context patterns that are more meaningful than any single dimension would be in isolation.

Configurational theories are a newly applied approach in the field of IS which are best suited for examining holistic interplays between elements of a messy, and non-linear nature [46]. The aim of configuration theory is to identify patterns and combinations of variables and reveal how their synergistic effects lead to specific outcomes. Configurations occur by different combinations of causal variables that affect an outcome of interest. The main difference of configuration theory is that it views elements through a holistic lens so that they must be examined simultaneously, and is therefore particularly attractive for context-related studies in which there is a complex causality. Contrarily to variance and process theories, configuration theory supports the concept of equifinality, meaning that the same outcome can be a result of one or more sets of configuration patterns. Additionally, configuration theory includes the notion of causal asymmetry, meaning that the combination of elements leading to the presence of an outcome may be different than those leading to an absence of the outcome [46].

4 Methodology

4.1 Data

To explore the combination of factors that lead to strong process innovation capabilities, a survey instrument was developed and administered to key informants within firms. We conducted a pre-test in a small-cycle study with 23 firms to examine the statistical properties of the measures. Through the pre-test procedure we were able to assess the face and content validity of items and to make sure that key respondents would be in place to comprehend the survey as intended. For the main study, we used a population of 500 firms from a list of Norway's largest companies, measured in terms of revenue (Kapital 500). Each of these firms was contacted by phone in order to get contact details of the most appropriate key respondent (e.g. chief information officer, chief technology officer) and inform them about the purpose of this research. 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 four months (February 2017 – July 2017), and on average completion time of the survey was 14 minutes. A total of 213 firms started to complete the survey, with 202 providing complete responses.

Table 1. Sample Characteristics

Factors	Sample (N = 202)	Proportion (%)
Industry		
Bank & Financials	28	13.8%
Consumer Goods	22	10.8%
Oil & Gas	21	10.4%
Industrials (Construction & Industrial goods)	19	9.4%
ICT and Telecommunications	11	5.4%

Technology	9	4.4%
Media	9	4.4%
Transport	8	3.9%
Other (Shipping, Consumer Services etc.)	75	37.1%
Firm size (Number of employees)		
1 – 9	1	0.5%
10 – 49	34	16.8%
50 – 249	36	17.8%
250+	131	64.8%

With non-response bias being a common problem in large-scale questionnaire studies, we took measures both during the collection of the data to ensure we had a representative response rate, as well as after the concluding of the data gathering. All participants were given an incentive to partake in the study, and were promised a personalized report benchmarking their firms' performance in a number of areas to industry means [47]. After the initial invitation to take part in the survey, respondents were re-contacted on three occasions with two-week interval between each reminder. After the data collection was finished, and to ensure that no bias existed within data, we compared between early and late responses at the construct level to verify that no significant differences existed. To do so, we constructed two groups of responses, those who replied within the first three weeks and those that replied in the final three weeks. Through t-test comparisons between group means, no significant differences were detected. In addition, no significant differences were found between responding and non-responding firms in terms of size and industry. Considering that all data were collected from a single source at one point in time, and that all data consisted of perceptions of key respondents, we controlled for common method bias following the guidelines of Chang, Van Witteloostuijn and Eden [48]. *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*, we used Harman's one factor test, which indicated that a single construct could not account for the majority of variance.

4.2 Construct Definition and Measurement

We build on the notion of big data analytics capability from the study of Gupta and George [8] to determine all relevant resources [49]. The concept distinguishes between the three underlying pillars which are big data-related tangible, human skills, and intangible resources. Each of these groups of factors is very distinct and comprises of a unique set of variables. Specifically, within the tangle big data resources, we distinguish between data, technology, and basic resources. With regards to human skills, we identify two mains categories, technical and managerial skills. Finally, in relation to intangible resources, we include a data-driven culture and the intensity of organizational learning as two core resources. Each of the previously mentioned concepts is measured on a 7-point Likert scale, in accordance to the study of Gupta and George [8]

The degree of environmental uncertainty was assessed through three measures; dynamism (DYN), heterogeneity (HET), and hostility (HOST) [50]. 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. All constructs were measured as latent variables on a 7-point Likert scale.

A process innovation capability is defined in the context of the skills and knowledge needed to effectively absorb, master and improve existing processes and to create new ones. We measured process innovation capability through two first-order latent construct; incremental process innovation capability (INC) and radical process innovation capability (RAD). Incremental process innovation capability was measured with three indicators assessing an organizations capability to reinforce and extend its existing expertise in processes. Likewise, radical process innovation capability was assessed through three indicators that asked respondents to evaluate their organization's ability to make current processes [36].

Firm size was measured as a binary variable in accordance with recommendations of the European Commission (2003/361/EC) with SME's including micro (0-9 employees), small (10-49 employees), and medium (50-249 employees) enterprises, and large being those with more than 250 employees. Large firms were assigned the value 1, while SME's were represented with 0. The industry was further grouped into product and service industries, in which 1 connotes a product industry, and 0 a service industry.

4.3 Reliability and Validity

Since the research design 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 gauged at the construct and item level. At the construct level we examined Composite Reliability (CR), and Cronbach Alpha (CA) values, and confirmed that their values were above the threshold of 0.70. Indicator reliability was assessed by examining if construct-to-item loadings were above the threshold of 0.70. To establish convergent validity, we examined if AVE values were above the lower limit of 0.50, with the smallest observed value being 0.59 which greatly exceeds this threshold. We examined for the presence of discriminant validity through three ways. The first looked at each constructs AVE square root to verify that it is greater than its highest correlation with any other construct (Fornell-Larcker criterion). The second tested if each indicator's outer loading was greater that its cross-loadings with other constructs [51]. Recently, Henseler, Ringle and Sarstedt [52] argued that a new criterion called the heterotrait-monotrait ratio (HTMT) is a better assessment indicator of discriminant validity. Values below 0.85 are an indication of sufficient discriminant validity, hence, the obtained results confirm discriminant validity. The abovementioned outcomes 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.

For formative indicators, we first examined the weights and significance of their association with their respective construct. While all of the indicators weights for data and basic resources were statistically significant, one of the three indicators weights (BR2) of the technology construct was found to be non-significant. According to

Cenfetelli and Bassellier [53], formative constructs are likely to have some indicators with non-significant weights. Their suggestion is that a non-significant indicator should be kept providing that the researchers can justify its importance. Since the technology construct is proposed as an aggregate of three items, where each captures a different big data-related technology, we believe that it is critical to include the indicator in the model as it makes a distinct contribution. A similar approach is followed by Gupta and George [8] in their operationalization of big data analytics capability. Next, to evaluate the validity of the items of formative constructs, we followed MacKenzie, Podsakoff and Podsakoff [54] and Schmiedel, Vom Brocke and Recker [55] guidelines using Edwards [56] 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, suggesting that the majority of variance is shared with the overarching construct, and that the indicators are valid representations of the construct. Next, we examined the level 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 Petter, Straub and Rai [57]. All values were below the threshold of 3.3 indicating an absence of mutlicollinearity.

5 Analysis

5.1 Methodology and Calibration

To determine what big data analytics resources are most important in the formation of process innovation capabilities among different environmental and contextual conditions, this study employs a fuzzy-set Qualitative Comparative Analysis (fsQCA). FsQCA follows the principles of configurational theories which allow for the examination of interplays that develop between elements of a messy and non-linear nature [58]. As such, it is important to isolate what combination of factors and conditions contribute towards firms developing strong incremental and radical process innovation capabilities. The first step of the fsQCA analysis is to calibrate dependent and independent variables into fuzzy or crisp sets. These fuzzy sets may range anywhere on the continuous scale from 0, which denotes an absence of set membership, to 1, which indicates full set membership. Crisp sets are more appropriate in categorical variables that have two, and only two options. The procedure followed of transforming continuous variables into fuzzy sets is grounded on the method proposed by Ragin [59]. According to the procedure, the degree of set membership is based on three anchor values. These represent a full set membership threshold value (fuzzy score = 0.95), a full non-membership value (fuzzy score = 0.05), and the crossover point (fuzzy score = 0.50) [60]. Since this study uses a 7-point Likert scale to measure constructs, the guidelines put forth by Ordanini, Parasuraman and Rubera [61] are followed to calibrate them into fuzzy sets. Therefore, full membership thresholds are set for values over 5.5, the cross over point is set at 4, and full non-membership values at 2.5. The size-class of firms is coded as 1 for large enterprises and 0 for SME’s, while product-based companies are marked with 1, and service-oriented ones with 0.

5.2 Results

We performed two separate fsQCA analyses, one for each dependent variables of interest, that is high incremental and radical process innovation capabilities. Each analysis produces a truth table of 2^k rows, where k represents the number of predictor elements, and each row stands for a possible combination (solution). Solutions that have a consistency level lower than 0.80 are disregarded [62]. In addition, a minimum of three cases for each solution is set [60]. Having established these parameters, the fsQCA analyses are then performed using high incremental and radical process innovation capabilities as the dependent variables. The outcomes of the fuzzy set analysis are presented in Table 2. The solutions are presented in the columns with the black circles (●) denoting the presence of a condition, the crossed-out circles (⊗) indicating an absence of it, while the blank spaces represent a "don't care" situation in which the causal condition may be either present or absent [63].

Table 2. Configurations for high incremental and radical process innovation capabilities

Configuration	Solution					
	Incremental Process Innovation Capability			Radical Process Innovation Capability		
	1	2	3	1	2	3
Big Data Analytics Resources						
Data	●	●	●	●	●	●
Technology	●					
Basic Resources		●	●			
Technical Skills	●	●	●	●		●
Managerial Skills				●	●	●
Organizational Learning					●	
Data-driven Culture					●	●
Environment						
Dynamism		●	●		●	●
Heterogeneity	●		●	●		
Hostility				●	●	
Context						
Size	●		●	●	●	⊗
Industry	●	⊗	⊗	●	⊗	⊗
Consistency	0.872	0.868	0.927	0.906	0.823	0.815
Raw Coverage	0.237	0.202	0.161	0.241	0.197	0.152
Unique Coverage	0.207	0.139	0.135	0.187	0.122	0.124
Overall Solution Consistency	0.825			0.841		
Overall Solution Coverage	0.479			0.427		

With regards to a firm's incremental innovation capabilities, solution 1 corresponds to large firms of a large size-class that operate in product-based industries, and with a business environment characterized by high heterogeneity. For these companies the presence of strong data, technology, and technical skills is found to be a solution for achieving high incremental process innovation capabilities. The next two solutions, 2 and 3, represent firms that are service-oriented. Specifically, in solution two, for companies that operate in dynamic environments, data and technical skills are found to be important, including the presence of solid basic resources. This solution is size-class independent, meaning that it could apply to either large firms or SME's. Solution 3 on the other hand concerns large firms in the service industry that operate in highly dynamic and heterogeneous environments. For these firms, the presence of strong data and basic resources, technology and technical skills is shown to lead to a high incremental process innovation capability. It is important to note that an appropriate lens to consider the ways these resources are leveraged in such environments is the dynamic capabilities view of the firm [64].

Concerning configurations that lead to high radical process innovation capabilities, there are also three solutions. Solution applies to firms that are in product-based industries and belong to the large size-class. The environment that they operate in is characterized by high heterogeneity and hostility. For these firms the presence of strong data resources, coupled with solid technical and managerial skills yields high radical process innovation capabilities. Solutions 2 and 3 correspond to service industry firms. Specifically, solution 2 is about large firms operating in dynamic and hostile conditions. In such settings, the presence of strong data resources, along with solid managerial skills, organizational learnings and a mature data-drive culture are the cornerstones of achieving high radical process innovation capabilities. Solution 3 on the other hand highlights the conditions for firms of the SME size-class, that conduct business in dynamic markets. These firms rely on the presence of strong data resources along with mature technical and managerial skills, and a solid data-drive culture.

6 Discussion

While much has been written about the strategic value of big data analytics, studies dedicated to empirical evidence on the real business value of such investments at the firm level remain scarce. Our understanding about, if, and how big data analytics can help support process innovation is still at a rudimentary state. To explore this topic, the present study built on a theory-driven conceptualization of big data analytics, and identified the main resources that underpin the notion. In addition, following literature on context-aware process design success factors, we explore how the context and big data analytics resources coalesce to drive firm process innovation capabilities. Grounded on a configurational theory approach that enables us to examine such interactions, we analyze responses from 202 IT managers of Norwegian firms and derive different solutions through which high levels of incremental and radical process innovation capabilities are attained.

From a theoretical perspective, the findings of this study add to existing literature in several ways. First, it demonstrates how a contingency approach can be empirically explored in the context of business process management. Such contextual factors are seldom investigated in quantitative studies with regards to business process innovation [10]. Second, despite much anecdotal claims concerning the enabling effect that big data analytics have on strengthening existing or developing new business processes, there is still limited empirical research to consolidate them [3]. Our findings show that different combinations of big data-related resources have a greater or lesser significance depending on the context and the type of process innovation capability they are targeted towards. More precisely, we find that more technological and technical resources contribute towards delivering incremental process innovation capabilities, whereas a firm-wide data-driven culture and strong managerial data analytic skills are critical when it comes to radical process innovation capabilities.

From a practical point of view these results suggest that managers should develop different strategies in relation to their big data analytics initiatives, depending on the types of business process innovation they aim to achieve, while also taking into account the contingencies of the environment and the organization. Specifically, the results suggest that when it comes to radical process innovation capabilities, data governance practices should encourage the breakdown of organizational silos and promote the notion of data-driven decision-making at all levels of the organization [65]. In addition, managerial knowledge on data-driven initiatives and the potential application of big data to organizational problems should be encouraged through targeted seminars and training. Contrarily, for incremental process innovations to emerge, managers should focus on technical excellence in terms of human skills and tangible resources. For these types of process innovations, strong technical skills are critical, since gaining insight to produce incremental improvements likely requires expertise in skills that are domain specific.

While the results of this study shed some light on the relationship of big data analytics resources and process innovation capabilities, they must be considered under their limitations. First, our sample comprises of companies operating in Norway and belonging to the 500 largest in terms of revenue. It is highly likely that firms that operate on a smaller scale will have different configurations of factors that drive process innovation capabilities. Second, while we differentiate between incremental and radical process innovations, we do not control for the different types of processes in terms of their domain area. The different functional areas in which big data analytics are applied are likely to yield different results and require varying configurations of resources to enhance or create innovative business processes. Third, although fsQCA allows us to examine the configurations of resources and the contextual factors under which they produce process innovation capabilities, the significance of each resource, as well as the process through which it produces this outcome is not well explained. A complementary study suing a qualitative approach would likely reveal more insight on how value is produced from such investments.

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Appendix A. Survey Instrument

The survey instrument can be found here: https://goo.gl/4y4QVr