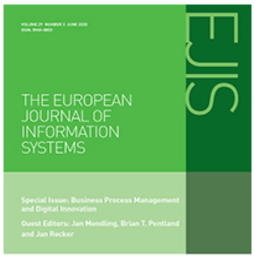

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Examining the interplay between big data analytics and contextual factors in driving process innovation capabilities

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ABSTRACT
The potential of big data analytics in enabling improvements in business processes has urged researchers and practitioners to understand if, and under what combination of conditions, such novel technologies can support the enactment and management of business processes. While there is much discussion around how big data analytics can impact a firm's incremental and radical process innovation capabilities, we still know very little about what big data analytics resources firms must invest in to drive such outcomes. To explore this topic, we ground this study on a theory-driven conceptualisation of big data analytics based on the resource-based view (RBV) of the firm. Based on this conceptualisation, we examine the fit between the big data analytics resources that underpin the notion, and their interplay with organisational contextual factors in driving a firm's incremental and radical process innovation capabilities. Survey data from 202 chief information officers and IT managers working in Norwegian firms are analysed by means of fuzzy set qualitative comparative analysis (fsQCA). Results show that under different combinations of contextual factors the significance of big data analytics resources varies, with specific configurations leading to high levels of incremental and radical process innovation capabilities.

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1. Introduction

The ability to generate actionable insight from large volumes of unstructured data has elevated the interest of managers and decision-makers in big data analytics (BDA) over the past few years (Davenport et al., 2012). It is argued that this data-generated insight is particularly relevant in dynamic and volatile business environments, where the need to continuously innovate is accentuated (Prescott, 2014). Recent studies have confirmed such claims, with findings indicating positive associations between investments in BDA and firm productivity, which are amplified in highly competitive industries (Müller et al., 2018). Positive outcomes have also been noted for several different domain areas and in terms of different indicators, ranging from supply chain performance, agility, and overall firm performance (Gunasekaran et al., 2017; Hassna & Lowry, 2018; Wamba et al., 2017). The increase of organisations deploying BDA to strengthen their process innovation capabilities has sparked the interest of recent research over the past few years, which has examined if, and under what combination of conditions BDA can produce business value (Mendling et al., 2017; Müller et al., 2016; Vom Brocke et al., 2014b).

Nevertheless, a recent report by Gartner forecasts that through 2020, 80% of BDA projects will not deliver business results and will not manage to make it into production (Gartner, 2019). The sizeable number of firms that are still struggling to realise process innovation or improvements from their BDA investments has ignited a debate about what BDA resources are most important to develop (Günther et al., 2017; Marr, 2016). Some recent investigations have shown that firms that focus on structured adoption of BDA realise performance gains (Gupta & George, 2016; Hassna & Lowry, 2018; P. Mikalef et al., 2019b; Müller et al., 2018; Wamba et al., 2017). These and several other studies provide support to the idea that BDA resources need to be cultivated based on the type of process innovation capability they are targeted towards (Bouncken et al., 2018; Liu et al., 2018), as well as on contextual factors of the environment and the organisation (Schmiedel et al., 2019; Zelt et al., 2019). Such findings also are in line with a growing body of research in business process management literature which advocates a holistic perspective (Rosemann & De Bruin, 2005; Vom Brocke & Rosemann, 2010; Vom Brocke et al., 2014b).

This view underscores the importance of complementary organisational factors when leveraging new digital technologies towards business process management and innovation (J. Recker & Mendling, 2016; Schmiedel et al., 2015; Trkman, 2010, 2013; Vom Brocke et al., 2016). Therefore, employing BDA to promote business process innovation, first requires identifying the business value-creating resources and the context in which they are

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more relevant (Anastassiu et al., 2016; Schmiedel & Vom Brocke, 2015; Trkman, 2010; Vom Brocke & Mendling, 2018; Vom Brocke et al., 2016). This argument is also advocated in practitioners' publications, where a one-size -fits-all approach to BDA is being challenged (Ransbotham & Kiron, 2017).

As such, the objective of the paper is to identify in what ways BDA resources complement with organisational factors and the environment towards the enhancement of process innovation capabilities. As firms compete in different contexts and under a unique set of constraints, the resource base that they develop will be shaped to fit the environment in which they operate (Drazin & Van de Ven, 1985). Research in the IS domain has shown that contextual factors of the organisational and external environment, as well as the types of outcomes that are pursued influence the IT resource arrangements that are selected to produce optimal fit with the environment (Mooney et al., 1996; Park et al., 2017; Sambamurthy & Zmud, 1999).

Grounded on this idea, we first draw a distinction between incremental and radical process innovation capabilities (Schniederjans, 2018), since the types of goals BDA are targeted towards are suggested to influence the importance of different combinations of resources needed to attain them (Vom Brocke et al., 2016). In this study, we define incremental process innovation capability as an organisational ability to reinforce and extend existing processes by significantly improving them, while a radical process innovation capability is the ability of a firm to introduce radically new processes that make existing processes obsolete (Gallouj & Savona, 2009; Subramaniam & Youndt, 2005). Furthermore, we include organisational and environmental factors in our examination. The organisational factors in this study involve aspects such as the size-class of firms and the resource bundling, while the external environmental captures the dynamism, hostility and heterogeneity of the markets in which firms operate and compete. Therefore, the research question that drives this study is as follows:

> ***RQ:*** *"What big data analytics resources and contextual factors of the organizational and external environment are relevant for realizing incremental and radical process innovation capabilities, and how do these elements combine to achieve their effects?"*

To address this research question in a more fine-grained fashion, we use the Resource-Based View (RBV) of the firm (Wernerfelt, 1984) as the underlying theoretical lens to identify the relevant BDA resources, and contingency theory to examine how contextual factors coalesce with the resources to drive incremental and radical process innovation capabilities. Building on a sample of 202 survey responses from IT managers in Norwegian firms, we employ a configurational approach and examine the patterns of elements that lead to high levels of incremental and radical process innovation capabilities. This is done through the methodological tool fsQCA, which facilitates a more nuanced view of the non-linear relationships between BDA resources, contextual factors, and their effect on process innovation capabilities.

The rest of the paper is structured as follows. In Section 2 we introduce the central concepts of this research, including the relevant BDA resources which are grounded on the RBV (Bharadwaj, 2000; Lehnert et al., 2016). In the same section, the notion of process innovation capability is introduced, and a conceptual distinction between incremental and radical process innovation capabilities is drawn. Finally, the role of contextual factors is discussed through the contingency theory lens, where we highlight some of the most important contextual elements in relation to process innovation capabilities. Section 3 outlines the methodology we employed, as well as how the data collection was carried out, what measurements were used, and the reliability and validity tests used to confirm their appropriateness. In Section 4 we present the results of the fsQCA analyses followed by sensitivity and predictive validity tests. Finally, in Section 5 we draw on the theoretical and practical implications of this study and outline some limitations.

2. Background

The relationship between digital technologies, such as big data analytics, and process management projects has been a topic of much debate over the past few years (Del Giudice et al., 2018; Vom Brocke & Rosemann, 2010). The consensus in the research community is that digital technologies act as enablers and facilitators of changes identified in process management projects (Trkman, 2010). Several research articles have begun to develop this idea on a more theoretically grounded basis, both in relation to the different types of resources that affect business process outcomes (Trkman, 2010), as well as on how the context shapes this relationship (Vom Brocke et al., 2016). The prevailing logic in these studies is that the implementation of any new digital technology in support of process management necessitates a broader view of the organisation, and an understanding of how other complementary resources can condition and shape outcomes (Dumas et al., 2013; Vom Brocke et al., 2014b). The literature now recognises that a number of complementary elements needs to be addressed in order to lead to successful and sustainable deployments in process management projects (Rosemann & Vom Brocke, 2015). An outcome of this perspective have been several maturity models, which attempt to outline the core areas and levels of change that need to be managed in order to lead to successful adapted or new process outcomes (De Bruin, 2009; Rosemann & De Bruin, 2005). Subsequently, other researchers have called for the inclusion of such factors in a holistic process management approach (Trkman, 2010; Vom Brocke et al., 2014b).

2.1. Big data analytics resources

On examining the potential business value of BDA, research has started to look into the challenges and complementary resources that firms must develop in order to be able to leverage their BDA investments (Mikalef et al., 2018b; Vidgen et al., 2017). It is now widely accepted that in order to derive any business value from big data, firms must also take into account the organisational fabric into which these technologies will be utilised and allocate the required resources to harness the insight that big data can deliver (Abbasi et al., 2016; Conboy et al., 2020). Empirical work looking into the impact that structured adoption of BDA overall has documented positive effects on organisational performance measures and key indicators (Côrte-Real et al., 2017; Gupta & George, 2016; Hassna & Lowry, 2018; Müller et al., 2018; Wamba et al., 2017). Nevertheless, there is scarce empirical evidence demonstrating the impact of BDA in strengthening a firm's process innovation capabilities (Wamba & Mishra, 2017). While some studies have explored how BDA have in specific case studies prompted changes in the processes of firms (Gomber et al., 2018; Lehrer et al., 2018), we still know very little about the configurations of resources that are required to achieve such outcomes, particularly in relation to the type of innovation that is pursued.

Understanding the impact BDA can have in enabling incremental and radical process innovation capabilities can allow firms to direct their investments and deployments accordingly and focus on areas that are of higher importance to them. Even more, there is an overarching assumption that BDA resources are equally important regardless of the context in which they are applied. Such one-size-fits-all approaches have been challenged by latest practice-based reports and research studies (Conboy et al., 2020; Ebner et al., 2014; Kiron, 2017; Mikalef et al., 2019a). In fact, it is argued that depending on the context in which BDA is applied, and the outcomes towards which it is directed, there is a need to adopt a different approach, and focus on a different combination of complementary resources to realise expected objectives (Ramanathan et al., 2017). We ground this research theoretically on the RBV, which posits that the resources a firms owns or has under its control can be leveraged strategically to confer a competitive advantage (Spanos & Lioukas, 2001). Since the aim of this study is to identify the main BDA resources that have an impact on process innovation capabilities, the choice of the RBV as the underlying theoretical framework is deemed as suitable.

Building on existing research that utilises the RBV to define types of resources that are relevant to business value from BDA investments (Gupta & George, 2016), we make a distinction between three broad types of resources: tangible, human skills, and intangible (Grant, 1991). With regard to tangible resources, data, technology and other basic resources are considered important pillars for success in the context of BDA deployments (Gupta & George, 2016). A common concern amongst IT strategists and data analysts is the quality and availability of the data they analyse (Janssen et al., 2017; Park et al., 2017). From an infrastructure point of view, it is also critical for firms to possess the necessary capacities for storing, sharing, and analysing data, as well as for analytic methods to turn data into insight (Mikalef et al., 2018b; Müller et al., 2018; Park et al., 2017). Furthermore, 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 outcomes (Günther et al., 2017).

Regarding the human factor, Wamba et al. (2017) recognise that technical and managerial skills are important to derive business value from big data investments (Wamba et al., 2017). Specifically, concerning technical skills, Davenport and Patil (2012) emphasise on the importance that the emerging job of the data scientist will have in the next few years throughout a number of industries. Such technical skills are important when it comes to understanding what data is of value, and how different data types can be cleansed, processed, and analysed to derive insights that are actionable (Costa & Santos, 2017). Nevertheless, 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 (Mikalef et al., 2018a; Prescott, 2014). Several studies underscore the importance of top management in driving big data initiatives and identifying areas where analytics can be utilised (Park et al., 2017; Vidgen et al., 2017). With data analytic techniques becoming increasingly more sophisticated, it is important that managers have the necessary knowledge to understand where they can be applied, and also how they can base their decisions on the generated insight to improve decision-making quality (Janssen et al., 2017).

In relation to intangible resources, a data-driven culture and organisational learning are widely regarded as important components of effective deployments of big data initiatives (Abbasi et al., 2016). 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 organisational strategy (Grover et al., 2018; LaValle et al., 2011).

A complementary facet is organisational 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 (Vidgen et al., 2017). These resources have been highlighted as being particularly relevant in the context of BDA, yet, there is still limited understanding on what combinations prove to be more important under different contexts, and in relation to different process innovation capabilities.

2.2. Process innovation capabilities

While business process management has predominantly focused on promoting incremental improvements through efficiency and effectiveness on business processes through standardisation, automation, and optimisation, there is a growing stream of research that highlights the potential for radical process innovations (J. C. Recker & Rosemann, 2015; Vom Brocke & Schmiedel, 2015). In today's dynamic globalised business arena, process innovation is important for several reasons. First, the business 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 (Adner & Levinthal, 2001). Second, process innovation is inextricable tied with product innovation (Adner & Levinthal, 2001). When companies need to introduce new products, there is a requirement to change existing processes, or even form new ones when they involve techniques that are novel to the firm. In their empirical investigation, Fritsch and Meschede (2001) 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. Therefore, facilitating process innovation results in positive spillover effects. Third, a lot of product-based industries have begun to adopt a servitization approach, where large parts of revenues are generated from the services provided around physical products (Kowalkowski et al., 2017). Therefore, designing and improving the processes that underpin these services are of high importance for competitiveness and sustained performance (Trkman et al., 2015).

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 business value for the firm (Hogan et al., 2011). We identify two main types of process innovation capabilities, incremental and radical (Ettlie et al., 1984). An incremental process innovation capability is defined as an organisation's ability to reinforce and extend its existing expertise in processes, by significantly enhancing or upgrading them (Gallouj & Savona, 2009). Incremental process innovations have been argued to enhance supply chain performance, enable greater levels of information sharing, and promote inter-functional cooperation (Schniederjans, 2018).

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 (Subramaniam & Youndt, 2005). Examples of radical process innovations include for instance, the implementation by Walmart in the 1990 s of satellite technology to support its supply chain and warehousing, which became a well-established supply chain innovation (Schniederjans, 2018). Based on this system, Walmart was able to integrate all segments of the company, as well as communication with suppliers in real-time, and to develop demand planning and inventory management based on live data.

Management literature, grounded on the RBV and adopting a contingency theory lens has argued that the type of innovation that is pursued (i.e., incremental or radical), will generate unique constellations of resources and conditions that lead to outcomes of interest (Beugelsdijk, 2008; Herrmann et al., 2006; Troilo et al., 2014). Literature on process management has a long tradition of examining methods and approaches for innovation. Nevertheless, recent studies that attempt to isolate the elements that underpin process innovation, underline the importance of taking into account a holistic view, including the role of digital technologies, culture, and people (Mendling et al., 2017; Rosemann & Vom Brocke, 2015), and adopting an evolutionary view of the firm to its environment in order to examine how the market conditions under which firms operate to influence the choice of resources that are needed to achieve business goals (Klun & Trkman, 2018).

When it comes to use of BDA in the organisational setting; distinguishing between incremental and radical process innovation capabilities has been argued as being an important differentiating factor of the corresponding BDA resources that are selected, as well as how socio-technical systems are constructed to support outcomes (Gomber et al., 2018; Lehrer et al., 2018). The prevailing argument in this direction is that digital technologies such as BDA are reprogrammable, so organisations explore configurations of technologies, people and processes in order to confront different types of innovation outcomes and goals (Lehrer et al., 2018).

Such efforts have signalled a shift towards a broader perspective in understanding process innovation, incorporating organisational and external contextual factors in investigations (T. Schmiedel et al., 2015; J. Vom Brocke et al., 2016). Organisational factors typically include resource structuring or capability building processes, whereas external factors concern the conditions of the market, such as the complexity or rate of change of customer preference and technologies. The main argument made is that process innovation capabilities emerge through the coalescing of key organisational resources, which need to be attuned to the requirements of market demands (Piening & Salge, 2015).

Big data analytics have been hailed as a key technological development in achieving such outcomes, with several research commentaries and empirical studies highlighting the facilitating role that structured adoptions may have on strengthening firms incremental and radical process innovation capabilities (Van der Aalst & Damiani, 2015). More precisely, in realising gains in terms of incremental processes, it is suggested that firms should place emphasis on acquiring quality data and investing in a strong technological infrastructure that can handle the requirements of the data processing value chain (Vera-Baquero et al., 2013). Furthermore, approaches such as process mining which build on big data sets from event logs to extract knowledge and discover, monitor and improve real processes, put a strong focus on the technical skills of the data scientist (Van Der Aalst, 2016).

On the other hand, when it comes to radical process innovations, it has been advocated that a top-down approach is more appropriate, where managerial support and skills are central, as well as a culture that supports such fundamental shifts (Das et al., 2018). These factors combined with a proactive ability to detect emerging opportunities and threats through targeted data-generated insight is argued to promote the emergence of radical process innovation capabilities (Erevelles et al., 2016). The role of BDA in facilitating incremental and radical process innovations is relevant in several different areas of applications, such as supply chain management, marketing, customer engagement and management, smart homes, smart health, smart cities, smart energy, and smart mobility (Mendling et al., 2017). Hence, understanding what resources firms should foster to support the strengthening of each type of process innovation capability is critical, especially when taking into account the heavy cost incurred with such deployments, and their importance in realising a competitive edge (Popovič et al., 2018).

2.3. Contextual factors

While the role of context has been researched extensively in the fields of information systems and organisational studies (Sambamurthy & Zmud, 1999), it is still at a very early stage in the field of process management (Vom Brocke et al., 2016). Although not explicitly the focus of many studies, contradicting findings pinpoint to contingent results (Vom Brocke et al., 2014b), placing the context of examination as an important aspect that should be taken into account 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 process implementations (Vom Brocke et al., 2014b; Zelt et al., 2019). This perspective is rooted in contingency theory (Donaldson, 2001), which assumes that there is no one universal best way to manage business processes, but rather, that management practices and resources should fit the organisation and the external environment (Vom Brocke et al., 2016). A closely related perspective is that of the theory of multiple contingencies (Gresov, 1989), which posits that outcomes of interest in organisations are simultaneously influenced by numerous contingency forces, whose effects might complement or counteract one another (Sambamurthy & Zmud, 1999).

Thus, the organisational design and the subsequent use of IS towards this are a product of the interplay among different contextual (or contingency) factors. Similar views on process innovation have been supported by studies that adopt a strategic management and organisational research perspective (Ortt & van der Duin, 2008). While the contingency perspective is well documented in IS studies, one of the main barriers in examining its impact regarding the effectiveness of technological innovations, lies in the challenge of including such factors in quantitative investigations. While such factors are often included in the form of interaction effects or moderators, capturing their interdependencies and non-linear dynamics is very challenging using conventional methods of quantitative analysis. This limitation has been largely overcome with the latest methodological approaches that build on the principles of configurational analysis (Fiss, 2011).

In identifying the contextual factors used in this study we build on the work of J. Vom Brocke et al. (2016) by including the contextual elements that are posited to condition outcomes of process management projects. Specifically, the authors suggest that business process management projects are contextually influenced by the goals of the process (i.e., if the goal is to enhance incremental or radical process innovation capabilities), the broader external business environment, and the specifics about the organisation where process innovation capabilities are developed.

A first contextual factor that is examined in this study is the goal of the organisation, since goals directly influence the business process management practices and resources that are most suitable (Vom Brocke et al., 2016). Several authors make the distinctions between exploitation and exploration, or else incremental and radical process innovation capabilities (Rosemann, 2014; Vom Brocke et al., 2015a). 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. Therefore, the outcome of interest, that is whether a firms incremental or radical process innovation capability is enhanced, serves as a contextual factor in our analysis.

Another important group of contextual factors have to do with the external environment of the organisation. Particularly, the dynamism, heterogeneity, and hostility of the environment are critical to consider, since under such condition's organisations need to reconfigure the way they operate and emphasise more on analytical and research capabilities. The impact of the environment, and particularly the dynamism and competition within the market, the rate of technological change, and the scarcity of key resources have been noted to significantly affect the types of resources that are important in business process management (Vom Brocke & Mendling, 2018).

Finally, a key group of contextual factors relate to the organisation itself. Based on contingency theory, the size of the organisation plays an important role since, typically, larger organisations require more formalised processes that cross-vertical and horizontal functions than smaller firms (Vom Brocke et al., 2016). In addition, firm size is usually a good proxy regarding the amount of slack resources a firm has to dispose in experimenting with new or improved ways of handling business processes (Hung, 2006). Finally, the 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 (Trkman, 2013).

When we consider these contextual factors in relation to BDA deployments towards the strengthening of process innovation capabilities, it is important to note that the approach needed to realise positive outcomes is likely to be dependent on different combinations of these elements (Ebner et al., 2014; Ekbia et al., 2015). Following this line of reasoning, several researchers have opened a debate about what resource configurations would best match desired goals, in the face of organisational and external conditions (Günther et al., 2017). For instance, Gillon et al. (2014) discuss about the importance of investing in the right technological infrastructure in large organisations that focus on incremental process innovations, whereas Tallon et al. (2013) underscore the weight of managerial skills as orchestrators of decentralised governance structures targeted towards radical process innovations, particularly in heterogeneous markets with different data requirements.

Furthermore, there is also a good reason to believe that depending on the size-class of firms, different strategies for leveraging BDA may be put in action. The argument here is that large firms usually have the resources needed to realise objectives by investing in necessary technology infrastructure and through the unique datasets they maintain, whereas firms in the SME size-class may be more heavily dependent on strong technical talent (Gillon et al., 2014). Therefore, depending on their context of deployment, we expect to identify different successful patterns of BDA resources towards the strengthening of incremental and radical process innovation capabilities (Loebbecke & Picot, 2015).

One of the limitations of these studies through is that they do not examine the interactions between all the previously mentioned contextual factors and how their interplays may condition outcomes. Focusing on a single contextual factor may also create inconsistencies in findings due to the omission of others that are important contributors. Hence, based on past empirical work and recent case reports, we anticipate that contextual factors of the organisational and external environment will have a conditioning impact of the significance of BDA resources, and their subsequent importance towards realising process innovation gains. To visualise these complex interactions, Figure 1 depicts the argued interplay between BDA resources, the environment and organisational factors in driving process innovation capabilities. The figure illustrates the complex and simultaneous interactions between all the elements and suggests that specific causal recipes will produce process innovation capabilities.

3. Methodology

3.1. 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 (Pöppelbuß et al., 2015). Especially in relation to the emerging area of BDA, 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 organisational factors and aspects of the environment in shaping these requirements (Ebner et al., 2014; Torres et al., 2018; Wamba et al., 2017). While it may be useful to consider separate elements of context and examine their influence on outcomes of process innovation, it is also important to research their combinations to derive contextual patterns that are more meaningful than any single dimension would be in isolation (Van de Ven et al., 2000). Contingency perspectives and subsequent literature on the effect of contextual factors highlight the importance of examining such elements simultaneously, as looking at these in isolation may yield biased results and obscure some important unobserved contingencies (Chakravarty et al., 2013).

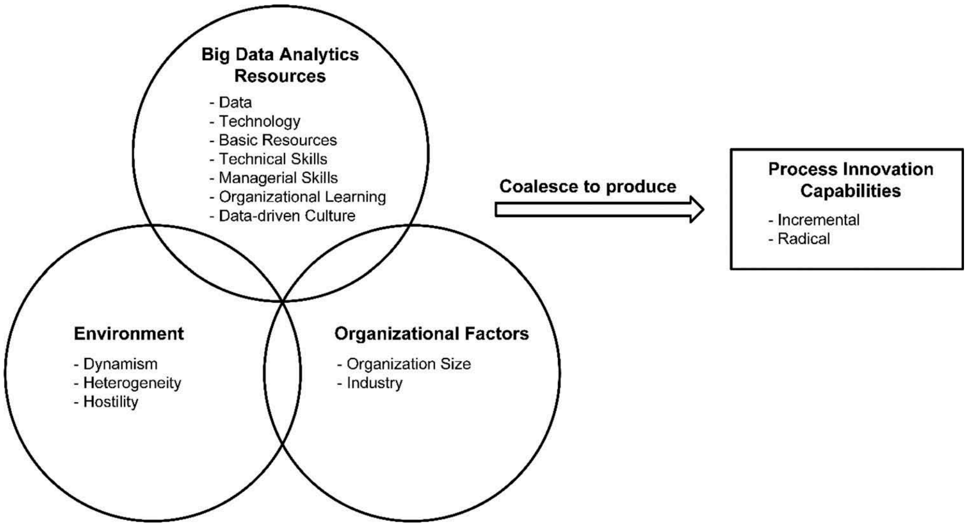

Figure 1. Research framework of configurations for driving process innovation capabilities.

Configurational methods are relatively new in the field of IS. They are best suited for examining holistic interplays between elements of a messy, and non-linear nature (Fiss, 2007). The aim of configurational methods 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 configurational methods 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 methods, configurational methods support the concept of equifinality, meaning that the same outcome can be a result of one or more sets of configuration patterns. Additionally, configurational methods include 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 (Fiss, 2007). In the last years, there has been a growing number of studies using configurational methods to examine contingency aspects in the domain of information systems research (Oyemomi et al., 2016; Park et al., 2017; El Sawy et al., 2010). These outcomes have enabled researchers and practitioners to identify how specific conditions influence the deployments of technological innovations, and to formulate appropriate strategies for assimilation (Ajamieh et al., 2016).

3.2. 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. The survey method was deemed appropriate to actualise the objectives of the study since it provides generalisationa of outcomes, allows for easy replication, and provides an effective way of exploring simultaneous relationships between a large number of factors (Pinsonneault & Kraemer, 1993). Straub et al. (2004) underscore the importance of survey-based research in exploratory settings and predictive theory. Furthermore, studies that employ configurational approaches of data analysis most commonly use survey data to explore firm-level phenomena (Fiss, 2011). One of the primary reasons for using survey data in such approaches is according to Fiss (2011), the capacity for survey-based methods to capture rich information regarding investments, strategy, the environment and performance.

Accordingly, for the purposes of this study a survey was developed that contained questions relating to investments in BDA resources, the structure and culture surrounding such technologies (Gupta & George, 2016), the environment (Newkirk & Lederer, 2006), as well as process innovation capabilities (Subramaniam & Youndt, 2005). The constructs and corresponding survey items used in this questionnaire, are largely based on previously published latent variables with psychometric properties that support their validity. All constructs and their corresponding items were developed on a 7-point likert scale, a well-established practice in the large-scale empirical research settings where no standardised measures exist for quantifying notions such as resources and capabilities (Kumar et al., 1993).

A small-cycle pre-test was conducted with 23 firms prior to the main study to determine the statistical properties of the measures. The firms contacted as part of the pre-test were not included in the final sample of responses and came from senior IT managers of companies operating in Norway. Respondents were contacted via email and asked to fill out an electronic version of the survey. 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. Furthermore, examples of key definitions were given to respondents including those of big data (i.e., “large structured and unstructured data sets that require new forms of processing capability to enable better decision making and are characterized by their volume, velocity, variety and veracity”), and BDA capabilities (i.e., “big data analytics capability is 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”), as well as the defining characteristics of big data through the four V’s of volume, variety, velocity, and veracity (Mikalef et al., 2018b). This was done to ensure that there was a uniform understanding of what was meant with the terms, and to guarantee that respondents had the same interpretation of questions.

After completing the questionnaire during the pre-test, respondents were contacted by phone and asked about the comprehensibility of questions and the clarity of the survey instrument. Based on the feedback received by respondents and the reliability and validity properties of items and constructs, some minor changes were made to reduce overlapping or similar questions, as for instance, including example technologies in questions (see item T1 in Appendix A). The reliability, validity, and statistical properties of the constructs were assessed using the software package SmartPLS 3.0 and were examined with the same criteria as in the main study. Regarding the phone interviews, the comments from each respondent were noted, and questions on specific items were asked as well as for the whole survey and its presentation. These notes in combination with reliability and validity outcomes of the statistical properties of measurements were the basis upon which decisions to retain or modify items were made. In addition, some minor modifications were made in the phrasing, presentation, and user interface of the survey instrument in response to feedback received.

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). Norway has been ranked as one of the most competitive nations in terms of international private industries, positioned at 11^{th} place world-wide according to the 2017–2018 Global Competitiveness Report of the Global Economic Forum (Schwab et al., 2017). In addition, Norway has very high levels of information and communication technology adoption, and a very dynamic business sector, rendering it a suitable environment to capitalise on the opportunities of the digital transformation (Baller et al., 2016). Each of the firms was initially contacted by phone 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. After the introductory phone contact, an email invitation was sent out to respondents to participate in the study and complete the online questionnaire, followed by two email reminders, each separated by a two-week interval.

To ensure a collective response, the respondents were instructed to consult other employees within their firms for information that they were not knowledgeable about. Furthermore, a personalised report was promised benchmarking each respondents company to country and industry averages obtained from the final data, in order to incentivise them to complete the survey and increase response rates (Sax et al., 2003). The data collection process lasted approximately 6 months (February 2017 – July 2017), and on the average completion time of the survey was 14 min. A total of 213 firms started to complete the survey, with 202 providing complete responses. The online questionnaire tool used allowed us to track respondents that started but did not complete the survey. Furthermore, there was the option of saving progress in the survey and continuing it at another time, which was as an effective way to reduce incomplete responses.

The final set of responses came from companies of a diverse industry background as depicted in Table 1. The largest proportion of the sample were firms operating in the banking and financial services sector (13.8%), followed by consumer goods (10.8%), oil & gas (10.4%),

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
Total Big Data Analytics Experience		
< 1 year	42	20.7
1–2 years	49	24.2
2–3 years	53	26.2
3–4 years	36	17.8
4+ years	22	10.8
Age of Company		
< 1 year	0	0.0
1–4 years	5	2.4
5–9 years	16	7.9
10–49 years	92	45.5
50+ years	89	44.0
Respondent’s position		
CEO/President	15	7.4
CIO	73	36.1
Head of Digital Strategy	42	20.8
Senior Vice President	33	16.3
IT Director	21	10.4
IT Manager	18	8.9

industrials (9.4%), while a large proportion came from a variety of other sectors (37.1%). The vast majority were large firms, accounting for 64.8% of the sample, while a considerably less, but still substantial amount came from SME's. The presence of SME's when looking at the data can be attributed to firms that are subsidiaries to larger parent companies. The respondents in our sample documented varied experience when it came to BDA projects, with most having 2–3 years of experience (26.2%). Furthermore, the respondents held positions that fit with our initial design, since they occupied roles bridging the business and IT domains within their firms.

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. Since all data were collected from a single respondent, we employed a series of measures to exclude the possibility of typical bias. To determine if there is a risk of method bias in our sample, we adhered to the guidelines of Podsakoff et al. (2003) and applied several measures to reduce the potential severity of common method bias. *Ex-ante*, respondents were assured that all information they provided would remain anonymous and confidential, and that any analysis would be done on an aggregate level for research purposes solely. *Ex-post*, we conducted a Harmon one-factor tests on the main variables of our study: data, technology, basic resources, managerial skills, technical skills, data-driven culture organisational learning, and incremental and radical process innovation capabilities. The results did not yield a uni-factor solution and the maximum variance explained by any one factor was 27.6%, a strong indication of an absence of common method bias.

In addition, to determine if there was any non-response bias in our sample, the profile of the respondents was compared with those on the mailing list we collected for each company, such as size and industry of operation. The chi-square analysis revealed no systematic response bias in the types of companies. In addition to non-response, we also examine late-response bias by comparing early (first 2 weeks) and late responses (last 2 weeks) through chi-square tests for firm size, industry, expenditure, and firm experience with big data, as well as for the main dimensions of the instruments that were used as part of the study. The outcomes showed that there were no statistically significant differences. Finally, we looked at within-industry differences in reported environmental uncertainty and found no statistically significant differences for the measures used in this study throughout the industries with a sufficiently large representation.

3.3. Construct definition and measurement

We build on the concept of BDA capability from the study of Gupta and George (2016) to determine all relevant resources (Mikalef & Krogstie, 2018). This 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 main categories, technical and managerial skills. Finally, in relation to intangible resources, we include a data-driven culture and the intensity of organisational learning as two core resources. Each of the previously mentioned concepts is measured on a 7-point Likert scale, following the study of Gupta and George (2016) but with a reduced set of items.

The degree of environmental uncertainty was assessed through three measures: dynamism (DYN), heterogeneity (HET), and hostility (HOST) (Newkirk & Lederer, 2006). 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 organisations 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 organisation's ability to make current processes obsolete (Subramaniam & Youndt, 2005).

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 where firms were divided into two mutually exclusive categories.

3.4. 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 0.62 which greatly exceeds this threshold. We examined for the presence of discriminant validity in 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 (Farrell, 2010) (Appendix B). Recently, Henseler et al. (2015) 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 (Appendix C). 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, as presented in Table 2.

For formative indicators, we first examined the weights and significance of their association with their corresponding construct. While all the indicators weights for data and technology resources were statistically significant, one of the two indicators weights (BR2) of the basic resources construct was found to be non-significant. Based on Cenfetelli and Bassellier (2009), formative constructs are likely to have some indicators with non-significant weights. Their recommendation is that a non-significant indicator should be kept providing that the researchers can justify its importance. Since BR2 items captures the time needed for BDA projects to deliver the value we have opted to keep it in the basic resources construct. Several empirical studies, as well as practice-based reports have indicated that BDA initiatives require time to mature and to produce value, so it is therefore considered as an important component of the overall capability and value creation mechanism (Conboy et al., 2020; Ransbotham et al., 2016). Gupta and George (2016) follow a similar approach in their operationalisation of BDA capability.

In sequence, to evaluate the validity of the items of formative constructs, we followed MacKenzie et al. (2011) and T. Schmiedel et al. (2014) guidelines using Edwards (2001) adequacy coefficient (R^2_a). To do so we summed the squared correlations between formative items and their respective formative construct and then divided the sum by the number of indicators. All R^2_a value exceeded the threshold of 0.50, suggesting that the majority of variance is shared with the overarching construct, and that the indicators are valid representations of the construct. Finally, 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 cut-off of 3.3 is used for formative constructs (Petter et al., 2007). All values in our study were below the threshold of 3.3 indicating that multicollinearity was not an issue, as shown in Table 3.

3.5. Set-theoretic Analysis with fsQCA

Following the configurational perspective that this study adopts, we use fuzzy-set qualitative comparative analysis (fsQCA), a set theoretic method, which can explore how key elements coalesce to explain an outcome of interest. Specifically, for the objectives of this research, fsQCA is deemed as a suitable tool to determine what BDA resources

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) Data	**n/a**											
(2) Basic Resources	0.288	**n/a**										
(3) Technology	0.571	0.243	**n/a**									
(4) Managerial Skills	0.561	0.427	0.370	**0.875**								
(5) Technical Skills	0.470	0.487	0.307	0.576	**0.947**							
(6) Data-driven Culture	0.269	0.322	0.222	0.307	0.343	**0.811**						
(7) Organisational Learning	0.529	0.365	0.384	0.513	0.376	0.356	**0.885**					
(8) Dynamism	0.217	0.276	0.296	0.286	0.225	0.384	0.346	**0.796**				
(9) Heterogeneity	0.277	0.222	0.255	0.438	0.310	0.278	0.421	0.485	**0.849**			
(10) Hostility	0.303	0.274	0.213	0.442	0.402	0.351	0.358	0.543	0.499	**0.802**		
(11) Incremental Process Innovation Capability	0.194	0.193	0.105	0.233	0.241	0.326	0.184	0.362	0.293	0.251	**0.789**	
(12) Radical Process Innovation Capability	0.351	0.433	0.351	0.339	0.348	0.346	0.363	0.374	0.401	0.282	0.441	**0.803**
Mean	4.62	4.16	4.21	4.39	4.24	4.45	4.71	4.12	3.94	4.01	4.43	4.25
Standard Deviation	1.80	1.72	2.01	1.64	1.71	1.53	1.41	1.45	1.39	1.43	1.48	1.54
AVE	n/a	n/a	n/a	0.77	0.90	0.66	0.78	0.63	0.72	0.64	0.62	0.64
Cronbach's Alpha	n/a	n/a	n/a	0.85	0.88	0.74	0.72	0.72	0.79	0.85	0.75	0.79
Composite Reliability	n/a	n/a	n/a	0.91	0.95	0.85	0.88	0.84	0.88	0.88	0.80	0.87

Table 3. Higher-order construct validation.

Construct	Measures	Weight	Significance	VIF	R^2_a
Data	D1	0.532	$p < 0.001$	1.164	0.78
	D2	0.327	$p < 0.01$	1.631	
	D3	0.570	$p < 0.001$	1.608	
Basic Resources	BR1	0.688	$p < 0.001$	2.137	0.73
	BR2	0.415	*n.s.*	2.260	
Technology	T1	0.299	$p < 0.01$	2.011	0.74
	T2	0.485	$p < 0.001$	1.552	
	T3	0.427	$p < 0.01$	2.032	

and contextual factors of the environment and the organisation are most important in the formation of incremental and radical process innovation capabilities. 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 (Fiss, 2011). As such, it enables us to isolate the combination of factors and conditions that contribute towards firms developing strong incremental and radical process innovation capabilities. Compared to variance-based methods that identify correlations between independent and dependent variables, fsQCA seeks patterns of elements that lead to a specific outcome. In addition, it enables the reduction of elements for each pattern, so configurations only include necessary, and sufficient conditions. Therefore, a distinction between core, peripheral and "don't care" aspects are developed, in which core and peripheral elements may be marked by their presence or their absence in explaining an outcome measure. Core elements are those that have a strong causal condition with the outcome of interest, while peripheral elements are those for which the causal relationship with the outcome is weaker (Fiss, 2011).

As a research approach, fsQCA presents several strengths when describing complex relationships between multiple elements, that are based on the use of set theory, Boolean algebra, and counterfactual analysis (Park et al., 2017). In effect, fsQCA can enable the identification of causal "recipes" that lead to an outcome of interest, and can extend beyond the conventional interaction term effects in regression analysis, which tend to be constrained to three-way interaction effects (Fiss, 2007). Therefore, fsQCA can handle complex multi-way interaction relationships in which all elements theoretically relevant to the outcome participate and can reduce the probability that unobserved heterogeneity may be a concern (Park et al., 2017). Furthermore, fsQCA can overcome some of the limitations of cluster analysis methods, which typically seek clusters of homogeneous cases based on empirical quantitative data, without a theoretical foundations and control over the outcome (Park et al., 2017). Thus, cluster analysis methods are limited in their ability to explain how clusters are formed. The main difference of fsQCA is that it allows researchers to select the outcome of interest and possible relevant causal variables, producing multiple bundles that lead to an outcome of interest (C. C. Ragin, 2009a). As such, it enables the examination of the specific combination of different elements in achieving such outcomes (Woodside, 2013).

3.6. Calibration

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 exactly two options. The procedure followed by transforming continuous variables into fuzzy sets is grounded on the direct method proposed by C. C. Ragin (2009a) and the suggestions of Schneider and Wagemann (2010). To do this we used the fsQCA 3.0 software package, which transforms a variable into a fuzzy set using the metric of log-odds and the distance of the variables value from the crossover point with the values of full membership and full non-membership as the upper and lower bounds (C. C. Ragin, 2009a). 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) (Park & El Sawy, 2013; Schneider & Wagemann, 2012; Woodside, 2013).

Since this study uses a 7-point Likert scale to measure constructs, the guidelines put forth by Ordanini et al. (2014) and Fiss (2011) are followed to calibrate them into fuzzy sets. Therefore, full membership thresholds are set for values over 5.5 of process innovation capabilities, the cross-over point is set at 4, and full non-membership values at 2. These thresholds are consistent with other empirical studies that transform 7-point likert scale variables into fuzzy sets, and due to distribution values based on the respondent bias to answer affirmatively (strongly agree) (Park et al., 2017; Schmitt et al., 2017; Tho & Trang, 2015). Descriptive statistics of construct means confirm this slight bias in distributions (left-skewness). These values were set for the main analysis (i.e., for high process innovation solutions), nevertheless, to further validate our calibration we conducted several sensitivity analyses. The same method of calibration is applied to the other variables used as predictors, with the only exception being the categorical ones of size-class and type of industry.

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. Firms were assigned mutually exclusive options in terms of their size (i.e., either large or SME) and industry type (i.e., either service or product-oriented). In doing so, we follow past empirical literature using fsQCA which uses mutually exclusive categories in the form of a binary variables for the purposes of the analysis, and to reduce the number of possible remainder rows (C. C. Ragin, 2005; Greckhamer et al., 2008). To make results more comprehensible, in the analysis section we have represented binary variables as two dummy variables (e.g., a value of 0 in the size-class variable is represented as a 1 in the item SME and a 0 in the item Large; we follow a similar approach towards the industry, product or service).

4. Analysis

We explored the combinations of BDA resources, as well as organisational and environmental factors that lead to high, very high, and low levels of process innovation capabilities. In each of the sub-sections below we discuss the results that were produced and the different solutions that emerged for both, incremental and radical process innovation capabilities. We performed two separate fsQCA analyses in each of the sub-sections, one for each dependent variable of interest, that is incremental and radical process innovation capabilities changing the calibration accordingly. 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 (Ragin, 2000, 2009b). Consistency refers to the degree to which cases correspond to the set-theoretic relationships expressed in a solution (Fiss, 2011). In other words, the consistency score explains how reliably a combination results in the outcomes, which is a measure roughly comparable to the significance level in the standard econometric analysis (Park et al., 2017).

In addition, a minimum of three cases for each solution is set (Park & El Sawy, 2013; Woodside, 2013). Having established these parameters, the fsQCA analyses are then performed using high incremental and radical process innovation capabilities as the dependent variables. The truth tables for each of the two outcome variables is presented in Appendix E along with the number of cases each solution is composed of (Fedorowicz et al., 2018; Park et al., 2017). The algorithm used in our analyses utilises Boolean algebra to logically reduce the truth table rows to simplified combinations. In this study, we apply the algorithm described by Ragin and Fiss (2008). This algorithm builds on a counterfactual analysis of causal conditions, which enable the distinction of causal conditions into core and peripheral causes. Core elements are thus considered to be essential towards the outcome of interest while peripheral ones can be regarded as expendable or exchangeable (Fiss, 2011). Researchers using fsQCA, therefore, view core elements as indicating strong causal relationships and peripheral ones as weaker predictors.

The fsQCA algorithm produces three different outcomes: parsimonious, intermediate, and complex solutions. However, to identify core and peripheral elements it is only necessary to examine the former two solutions (i.e., parsimonious and intermediate). Core conditions and those that are part of both parsimonious and intermediate solutions, while peripheral conditions are eliminated in the parsimonious solution and thus only appear in the intermediate solutions (Fiss, 2011). The outcomes of the fuzzy-set analyses are presented in the tables that follow in each of the following sub-sections. 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 (P. Mikalef et al., 2015). Large circles denote core conditions while small circles are an indication of a peripheral condition. The solutions in each set of analyses are grouped by their core conditions.

4.1. Configurations for high process innovation capabilities

The solution table (Table 4) shows that the fuzzy-set analysis results in three solutions for each type of process innovation capability. The solutions in each exhibit consistency values above the set threshold and include both core and peripheral elements. Solutions are assessed based on their consistency levels, raw and unique coverage, as well as on the overall solution consistency and coverage. As described earlier, consistency refers to the degree to which cases correspond to the set-theoretic relationships expressed in a solution (Fiss, 2011). According to C. C. Ragin (2009a), consistency is defined as the degree to which the cases sharing a given combination of conditions agree in displaying the outcome in question. In other words, consistency represents the extent to which a causal solution leads to an outcome and can range from 0 to 1 (Skarmeas et al., 2014). Solutions with high consistency scores indicate pathways that almost always lead to the given outcome condition (Elliott, 2013). Whereas consistency refers to individual solutions, overall solution consistency measures the degree to which all solutions together consistently result in the outcomes of interest; in this case high levels of incremental and radical process innovation capabilities (Park et al., 2017).

Coverage, on the other hand, indicates how many cases in the dataset that have high membership in the outcome condition are represented by a particular solution (Skarmeas et al., 2014). Effectively, coverage is a coefficient that expresses how much of the outcomes is covered, or explained, by a particular solution (Ragin, 2009a). The empirical importance of individual solutions is gauged by examining the raw coverage and unique coverage (Ragin, 2006). Raw coverage indicates which share of the outcome is explained by the specific solution, whereas unique coverage indicates which share of the outcomes is *exclusively* explained by the specific solution (Schneider & Wagemann, 2010). Similarly, overall solution coverage provides an indication as to what extent the outcomes of interest can be determined based on the extracted set of solutions. The measure of consistency is therefore analogous to a correlation coefficient, and the measure of coverage is analogous to the coefficient of determination (Woodside, 2013).

The solutions provided in Table 4 for achieving high levels of incremental and radical process innovation capabilities indicate the presence of both core and peripheral conditions, as well as neutral permutations for three of the configurations. Specifically, two of the solutions (2 and 3) for incremental process innovation capabilities present neutral permutations, while for radical process innovation capabilities there is one solution that presents neutral permutations (i.e., Solution 3). The notion of neutral permutations suggests that within a given configuration, there may be more than one constellation of different peripheral causes surrounding the core causal condition, with these permutations of peripheral elements being similarly effective in explaining the outcome of interest (Fiss, 2011). These outcomes and the identification of several alternative solutions leading to high levels of incremental and radical process innovation capabilities, respectively, are an indication of first-order, or across-type equifinality. In addition, the presence of neutral permutations within both types of process innovation capabilities points out to the existence of second-order, or within type equifinality (Fiss, 2011). Specifically, in Table 4 solutions are enumerated for achieving high levels of incremental and radical process innovation capabilities. Core solutions are grouped under an integer in each column (1, 2 and 3), while mutual permutations are marked with letters denoting the different constellations of peripheral conditions that develop around core Solutions, such as 2a and 2b. Each column, therefore, presents a unique solution towards the respective outcome.

Solution 1 under high levels of incremental process innovation capability depicts large black circles for data, technology, technical skills, heterogeneity, large firms and product industry. This means that the presence of these aspects is a core condition for achieving high levels of incremental process innovation capabilities. Small circles indicate peripheral conditions, and in this case, small circles are blank with a cross-out, meaning that their absence is of peripheral importance. In the case of Solution 1 we see that there are small crossed-out circles for basic resources, managerial skills, data-driven culture, dynamism and hostility. This means that the absence of the aspects has a contributing, but the weaker effect on the outcome of interest. In more detail, when looking at solutions that lead to high levels of incremental innovation capabilities, Solution 1 corresponds to firms that belong to the large size-class and which operate in

Table 4. Configurations for high incremental and radical process innovation capabilities.

	Solution								
	Incremental process innovation capability					Radical Process Innovation Capability			
Configuration	1	2a	2b	3a	3b	1	2	3a	3b
Big data analytics resources									
Data	●	●	●	●	●	●	●	●	●
Technology	●	•		•		•		•	
Basic resources	⊗	●	●	●	●	•	•		
Technical skills	●	●	●	●	●	●		●	●
Managerial skills	⊗	•	⊗	•		●	●	●	●
Organisational learning			•		•	⊗	●		•
Data-driven culture	⊗		•		•	⊗	●	●	●
Environment									
Dynamism	⊗	●	●	●	●	⊗	●	●	●
Heterogeneity	●	⊗		●	●	●	⊗	⊗	
Hostility	⊗		⊗	⊗		●	●	⊗	•
Organisational Factors									
Large firms	●	⊗	⊗	●	●	●	●		
SME’s								●	●
Product industry	●					●			
Service industry		●	●	●	●		●	●	●
Consistency	0.87	0.88	0.88	0.93	0.93	0.91	0.83	0.82	0.82
Raw coverage	0.24	0.20	0.17	0.16	0.16	0.24	0.19	0.15	0.15
Unique coverage	0.21	0.08	0.05	0.07	0.04	0.18	0.12	0.07	0.03
Overall solution consistency			0.83				0.83		
Overall solution coverage			0.48				0.43		

product-based industries. This solution suggests that under conditions of high heterogeneity, or else highly complex and diversified markets, and in the absence of environmental dynamism and hostility, there are certain resources that are fundamental in driving high levels of incremental process innovation capabilities. Specifically, this solution shows that by developing strong technical skills of employees and investing in data and technological infrastructure to store and analyse data and visualise insight, firms can strengthen their capacity to produce incremental process improvements. Furthermore, this can be achieved even in the absence of managerial skills to drive business analytics initiatives, without the need to establish a data-driven culture, and with limited financial resources to allow such projects to mature. This solution indicates that improvements facilitated through analytics are largely driven by the technical staff of companies, which combined with the product-oriented nature and size-class of firms, hint towards insight that are geared towards improving operational efficiency (e.g., manufacturing process, supply chain management). In fact, when considering that these firms operate in highly heterogeneous environments where firms need to have a diverse product portfolio, it is likely that analytics can help generate insight that identifies suboptimal operations that would be difficult to locate otherwise. Solution 1 demonstrates high levels of consistency (consistency = 0.87) and explain a substantial amount of cases (coverage = 0.24).

Solutions 2a and 2b indicate that companies that are not large and that operate in service industries that are characterised by conditions of increased dynamism can achieve high incremental process innovation capabilities by focusing on data, basic resources, and technical skills (core conditions). These solutions have a high degree of similarity to Solution 1, with the difference being that instead of highly complex markets, they are applicable for firms operating in fast-paced and dynamic conditions. Here we see the focus has shifted from having the necessary technological infrastructure, to investing in other basic resources. This highlights the importance of financial resources, as well as time to mature analytics projects for service industry firms, specifically for incremental process innovation capabilities. Furthermore, Solutions 2a and 2b suggest that there are trade-offs between focusing on strong managerial capabilities, and a more firm-wide approach when it comes to big data projects. Specifically, Solution 2a shows that in the absence of heterogeneity, strong managerial skills can suffice to drive incremental process innovation capabilities providing core conditions are present, while Solution 2b indicates that in low hostility environments, even an absence of managerial skills can lead to high incremental process innovation provided there is a strong data-driven culture and a propensity towards organisational learning. Solutions 2a and 2b demonstrate high levels of consistency (consistency = 0.88 for both), and satisfactory coverage of 0.20 and 0.17, respectively.

Finally, Solutions 3a and 3b indicate an important path to high incremental process innovation capabilities for large firms that compete in the service industry. In terms of the environment, both solutions concern firms that operate in highly competitive conditions, characterised by high dynamism and heterogeneity. In such environments, the combination of data, basic resources and technical skills is found to be a core configuration that leads to high incremental process innovation capabilities. When considering peripheral conditions, Solution 3a (consistency = 0.93; coverage = 0.16) combines the presence of technological infrastructure, managerial skills, and a lack of hostility in the environment, while Solution 3b (consistency = 0.93; coverage = 0.16) indicates that when hostility is not an important issue the presence of a data-driven culture and a focus on organisational learning can yield positive outcomes. These two solutions demonstrate the two alternative paths firms can opt for when operating under similar conditions.

The table also lists coverage scores which are an indication of the percentage of cases that lead to the selected outcome of interest (i.e., high incremental process innovation capability). The combination of the different solutions accounts for approximately 48% of the membership in the outcome. Yet, despite this high number it also indicates that there is substantial diversity within configurations that lead to high incremental process innovation capabilities. Across all solutions the models indicate the existence of two core conditions that are recurring. These are the existence of strong data resources to apply analytics on, and the necessary technical skills to capture, cleanse, store, analyse data and visualise insight. Overall, the solution for achieving high levels of incremental process innovation capabilities has a high consistency of 0.83 and a satisfactory coverage of 0.48.

With regards to solutions that lead to high levels of radical process innovation capabilities, Solution 1 concerns firms that operate in product-based industries, characterised by high heterogeneity and hostility and that belong to the large size-class. For these firms the presence of strong data resources, coupled with solid technical and managerial skills is core conditions for achieving high radical process innovation capabilities. This solution also suggests, that with an absence of a data-driven culture and limited focus on organisational learning, the presence of strong technological infrastructure and other basic resources coalesces to drive radical process innovation capabilities. It is interesting to note that the presence of strong managerial capabilities in big data projects is consistently found to be an important part of solutions in radical, but not in incremental process innovation capabilities, which highlights the importance that these skillsets have on prompting radical innovations. In addition, the first solution corresponds to large companies that despite operating in conditions of high complexity and limited resources do not face strong dynamism. This hints towards industries which most probably produce or trade commodities where the products do not become obsolete fast. Solution 1 demonstrates high levels of consistency (consistency = 0.91) and amongst the other solutions also presents the largest coverage (coverage = 0.24).

Solution 2, on the other hand, corresponds to firms that are competing in the services industry and are of a large size-class. The conditions in which these firms operate in are characterised by the presence of dynamism and hostility and with an absence of heterogeneity as a condition of lesser importance. In such settings, the existence of strong data resources, along with solid managerial skills, organisational learnings and a mature data-driven culture are the cornerstones of achieving high radical process innovation capabilities. Furthermore, this solution demonstrates that as a peripheral condition the presence of basic resources to support such capabilities is important regardless of if there is a focus on technological infrastructure and technical skills. This solution is also fairly consistent (consistency = 0.83) and has a significant coverage of 0.19.

Finally, Solutions 3a and 3b highlight a third important path to realising high radical process innovation capabilities for firms that are in the SME size-class and operate in service-based industries. In terms of the environment, high dynamism is the core feature of this cluster of firms, with Solution 3a (consistency = 0.82; coverage = 0.15) differing slightly from 3b (consistency = 0.82; coverage = 0.15) as it indicates an absence of heterogeneity combined with low hostility as peripheral conditions. Solution 3b, on the other hand, concerns high hostility as a peripheral condition regardless of whether there is high heterogeneity. Both solutions indicate that firms rely on the presence of strong data resources along with mature technical and managerial skills, and a solid data-drive culture. Comparing solutions though reveals that while technological infrastructure is a peripheral condition under the specific combination of external conditions in solution 3a, it is not found to be of importance in Solution 3b where a propensity towards organisational learning is found to exert a peripheral effect. The solution has a solid consistency of 0.83 and a satisfactory coverage of 0.43.

It is interesting to note that when it comes to radical process innovation capabilities, a different set of key resources emerges. These include, for instance, the presence of strong managerial capabilities. This outcome can denote that when it comes to incremental improvements strong managerial direction may not be necessary, whereas in circumstances where radical process innovation is the goal it is important to have managerial competences in BDA in order to direct efforts. Similar observations, but to a lesser extent, can be made on the more intangible aspects of BDA such as a data-driven culture and organisational learning, specifically for firms in the service industry and with regards to incremental process innovation capabilities. These outcomes show that the approach required to develop radical process innovation capabilities is deeply tied to governance schemes used to achieve them in a proportion of firms. Having said that, building a data-driven culture is an effortful task, which should be well-designed and implemented in order to succeed. This is a requirement for firms of the service industry, particularly if the goal is to develop radical process innovations, where data silos formed by different departments or where other organisational barriers may hinder the attainment of such outcomes.

4.2. Configurations for Very High Process Innovation Capabilities

To examine what combinations of conditions and resources lead to very high levels of incremental and radical process innovation capabilities, we adjusted the threshold for full set-membership of both corresponding variables to 6.5. The assumption, in line with the reasoning of Fiss (2011) is that different typologies lead to different types of outcomes. In the context of this study, this means that there may exist a different set of conditions that lead to very high outcomes in terms of process innovation capabilities, and that these can differ from those found for high performing configurations. Indeed, as depicted in Table 5, the results indicate one solution for each type of process innovation capability, with that of incremental process innovation capabilities presenting a mutual permutation.

In terms of very high incremental process innovation capabilities, outcomes of the analyses suggest that there is one core solution with two mutual permutations. Solutions 1a and 1b concern large firms that operate in the service industry. Achieving such outcomes requires that firms operate in high heterogeneity environments and rely on strong data investments, have focused on hiring or training employees with the necessary technical and managerial skills, and have infused a logic of organisational learning. The solutions also suggest some trade-offs, where firms that operate in dynamic, but not hostile environments, benefit by fostering a robust data-driven culture (solution 1a), whereas those that compete in hostile environments benefit by possessing other basic resources such as financing and time to develop BDA projects (solution 1b). The solutions corresponding to very high levels of incremental process innovation

Table 5. Configurations for very high incremental and radical process innovation capabilities.

	Solution		
	Incremental process innovation capability		Radical Process Innovation Capability
Configuration	1a	1b	1
Big data analytics rResources			
Data	●	●	•
Technology			
Basic resources		•	
Technical skills	●	●	•
Managerial skills	●	●	●
Organisational learning	●	●	●
Data-driven culture	•		●
Environment			
Dynamism	•		●
Heterogeneity	●	●	●
Hostility	⊗	•	⊗
Organisational Factors			
Large firms	●	●	●
SME's			
Product industry			
Service industry	●	●	
Consistency	0.91	0.91	0.90
Raw coverage	0.15	0.19	0.18
Unique coverage	0.05	0.06	0.08
Overall solution consistency		0.89	0.90
Overall solution coverage		0.24	0.22

capabilities account for 24% of membership in the outcome, suggesting that many firms that achieve such outcomes do so in rather diverse ways. Both solutions also present high levels of consistency with a value of 0.91 for each. In addition, the overall solution consistency is satisfactory (consistency = 0.89) and presents a fair amount of coverage (coverage = 0.24).

When examining solutions that lead to very high levels of radical process innovation capabilities, the fsQCA analysis reveals that there is one solution with sufficient consistency that can explain such outcomes (consistency = 0.90; coverage = 0.18). This solution is applicable for firms of the large size-class regardless if they are in the product or service industry. The environment for such cases is characterised by high heterogeneity and dynamism, and a lack of hostility. Under this combination of external conditions, establishing strong managerial skills and promoting a culture of data-driven decision-making and a climate that facilitates organisational learning are noted as core conditions. As peripheral conditions, the access to data combined with the human technical capacity to analyse them coalesce to drive very high levels of radical process innovation capabilities. In this solution, 22% of the membership is accounted for in the outcome, again demonstrating that there are several other, more fragmented and less consistent solutions to achieving such outcomes. What is interesting to note when examining solutions that lead to very high levels of incremental and radical process innovation capabilities, however, is that a propensity for organisational learning is consistently found to be a core condition. This finding is consistent with past work highlighting the important role that organisational learning has in acquiring, assimilating and exploiting knowledge and transforming this knowledge into process innovations (Jiménez-Jiménez & Sanz-Valle, 2011).

4.3. Configurations for Low Process Innovation Capabilities

As the different configurations that emerge when comparing high and very high level of process innovation capabilities demonstrate that there is an asymmetry in the causality of solutions, it is interesting to examine those that lead to low-performing outcomes. As high and very high configurations may provide a roadmap to achieving desired results from investments in BDA, so may low-performing solutions operate as a signal to practitioners to avoid developing strategies that focus on the wrong combinations of BDA resources in the wrong contexts. To perform this analysis the thresholds were reversed for each set-membership. Specifically, we conducted two types of analyses, one on the negated values of high process innovation capabilities, and a second one where thresholds values for full-membership were set equal or below to 2.5 on the 7-point likert scale. The findings indicate that when looking for configurations of low process innovation capabilities, there are no sufficiently consistent configurations that can explain outcomes, as the highest value of consistency in the truth table was below the 0.80 threshold. These outcomes suggest that there is an absence of a clear set-theoretic relationship when looking for low levels of process innovation capabilities. In other words, there is no consistent pattern of elements detected in firms where despite investing in BDA resources, they still realise low levels of process innovation capabilities.

4.4. Predictive Validity and Sensitivity Analyses

To verify that the outcomes of the fsQCA analyses have sufficient predictive validity, we followed the approach proposed by Woodside (2013). Accordingly, we split the sample into two equal sub-samples through random selection. Sub-sample 1 comprises the so-called modelling sample, while sub-sample 2 the holdout sample (Ali et al., 2016). An fsQCA analysis is executed for the modelling sub-sample applying the same observation number thresholds and consistency levels as in the main analysis. This is done for each of the two respective outcomes variables (i.e., incremental and radical process innovation capabilities) (Appendix D). The configurations that are produced by the modelling sub-sample are then tested on the data of the holdout sample by plotting each model on its respective outcome variables. The measures of consistency and coverage for all solutions are a strong indication that the models have high predictive abilities. To further validate the robustness of the outcomes produced by the fsQCA analyses, several sensitivity tests were performed changing the cross-over points and thresholds of membership for the outcome variables and the conditions.

Following past empirical studies that conduct such analyses to verify results, we adjusted thresholds for all variables using several different approaches. First, we used percentiles as an alternative approach for setting thresholds. Specifically, we computed percentiles so that the upper 25th percentiles serve as the threshold for full membership, the lower 25th percentiles for full non-membership, and the 50th percentiles for cross-over points. These were computed individually for each variable. Second, we used adjusted values around the ones set for the main analysis, adding and subtracting, respectively, 0.25 from the threshold values to determine if any significant changes were noted. Minor changes were observed in results with regards to the peripheral conditions that occur as well as the specific number of cases within solutions, but the interpretation of results remained largely unchanged. From the results obtained we concluded that outcomes were very similar, which indicates that our calibration method was appropriate and robust.

5. Discussion

5.1. Theoretical implications

The findings of this study add to the existing literature in several ways. Results empirically showcase the value that insight-generating tools such BDA can have on enabling both incremental and radical process innovation capabilities. The importance of such methods in creating insight which can lead to adaptation to an existing process or the creation of new ones has been highlighted in the literature (Rosemann & Vom Brocke, 2015; Vom Brocke et al., 2014a; Vom Brocke & Mendling, 2018). To date, we still know very little about the effect that such BDA resources can have on incremental and radical process innovation capabilities (Wamba, 2017), and in particular, how they coalesce with relevant contextual factors. The different solutions for achieving high levels of incremental and radical process innovation capabilities also demonstrated certain commonalities and some striking differences. For instance, the importance of emphasising on the data resource was found throughout all solutions for both types of process innovation capabilities. This finding is consistent with past studies that highlight the importance of being able to capture and store data that can lead to meaningful insight (Dezi et al., 2018). The value of developing the data resource has been suggested to be two-fold depending on the types of processes it is leveraged towards. Big data can allow processes to be streamlined and bottlenecks to be reduced, thus increasing efficiency (Davenport, 2014; Lu & Ramamurthy, 2011).

On the other hand, big data can enable managers to identify untapped insight, as for instance, in the case of customer behavioural patterns, and tailor radically new business processes, thus facilitating greater experimentation (Motamarri et al., 2017). Furthermore, big data can be aligned with existing business intelligence tools that are used to provide intelligent aid for organisational processes (Dezi et al., 2018). Park et al. (2017) show that the presence of such tools can positively influence different forms of organisational agility, with big data being a core input for generating meaningful insight. The only exception of the central importance of the data resource is in relation to achieving very high levels of process innovation capabilities. In Solution 1, presented in Table 5, the data resource has a peripheral role. This can be attributed to the fact that for organisations that strive for achieving very high levels of process innovation capabilities, the data resource itself will be less of a distinguishing factor. The core differentiators in such cases will rather be managerial insight and collective intelligence in the form of organisational learning and a data-driven culture. This outcome could indicate that the data resource can provide a competitive edge in terms of developing radical process innovation capabilities, but only up to a certain point. After that, it is the insight and creativity of managers, coupled with the complementary organisational resource that provide firms with an edge over their competition.

Another interesting point in the analysis is that when it comes to incremental process innovation capabilities, a stronger emphasis on technical skills and other basic resources are found to be core contributors. In fact, technical skills are required throughout all solutions for achieving high levels of incremental process innovation capabilities. Basic resources, on the other hand, are steadily central under conditions of dynamism and for companies operating in the service industry. The later result can be interpreted that in conditions of rapid change and fast-paced operating environments, analytics initiatives may need time and other financial resources to attune to the requirements of the external environment. A noticeable difference in the set of solutions for high incremental process innovation capabilities is Solution 1, which accounts for the largest proportion of cases. This solution corresponds to large firms operating in highly heterogeneous product industries, where data, technology and technical skills are central to realising high levels of incremental process innovation capabilities. It is interesting to note that this is the sole solution for firms operating in the product industry, and that in comparison with the other solutions which represent firms in the service industry, this cluster of firms appears to be more consistent in the elements that are important. In addition, the fact that companies of Solution 1 operate in highly complex and diversified environments that are product-based and belong to the large size-class, demonstrates the heightened importance of a strong technological infrastructure to handle and analyse large amounts of data. While much research has discussed the importance of the technological infrastructure (Chen et al., 2012), it has not identified for what types of firms and under what conditions such investments are more important. This is a particularly critical issue, as investments in the technological infrastructure for BDA bear huge costs for organisations that adopt them (Wang & Hajli, 2017).

For radical process innovation capabilities, it is striking to observe that there is a shift towards managerial skills as a core condition. In fact, for all solutions the concurrent presence of solid data resources coupled with strong managerial skills are core contributors in realising high levels of radical process innovation capabilities. This finding highlights the importance of having a strong managerial focus if radical process innovation capabilities need to be strengthened. Additionally, what is interesting to observe is that despite a data-driven culture being a central part in almost all solutions, it is not an important component in Solution 1. This can be explained by the fact that in conditions where there is high heterogeneity, decentralised line units that are mostly reliant on managerial competence are more likely to sustain radical process innovations, rather than a firm-wide culture. The idea of decentralised management practices in the face of diversified product-based industries is also in coherence with innovation management literature, which argues that in complex environments there is a stronger reliance on flexible management systems and on competent leadership (Chiesa et al., 2009). As in the solution for incremental process innovation capabilities (Solution 1), we see that product-based firms diverge from the norm, and cluster around a uniform solution. It is probable that due to the nature of the business environment, there is a stronger need for technical skills in analysing data and managerial skills for applying data towards radical solutions, rather than a firm-wide data-driven culture. This is reflected by the fact that in highly heterogeneous and product-based environments, product design and development as well as respective IT decision rights are handled in a decentralised business unit level structure (Tiwana & Konsynski, 2010).

While our findings confirm past work regarding the need for a managerial capacity to understand and coordinate data-driven insight in product innovation management (Slater et al., 2014), they also indicate that a strong data-driven culture is not a core requirement. This finding could hint that in heterogeneous conditions, where decentralised business units are favoured, radical process innovation capabilities do not emerge so much from a firm-wide culture or highly formalised routines for learning but more on informal practices or on abilities and the flair of individuals. Such notions have been laid out in the innovation literature which posits that most human learning that is directly associated with radical innovations occurs as non-formal learning (Casey, 2005; Lumpkin, 2014). In fact, the greater the decentralisation and local autonomy, the more likely it is that individuals will possess the most current and relevant marketing and technical knowledge. Hence, they will be more likely to deliver radical product innovations through data analytics (Slater et al., 2014). This difference between the product and service-based companies in terms of the importance of a shared culture regarding data-driven decisions is also noted in the innovation literature. According to this body of research, organisational aspects and a shared vision are more important contributors for service-based firms than for product-based ones (Nijssen et al., 2006).

For the remaining solutions that correspond to service industry firms, our findings highlight the importance of a data-driven culture. In fact, for large firms (Solution 2), the presence of an orientation towards organisational learning is marked as central, as acquiring knowledge and exploiting existing organisational competencies is critical in diffusing knowledge and strengthening radical process innovation capabilities, particularly in hostile conditions where resource scarcity and tough competition are prevalent. Our findings also align with prior studies in service-dominant firms, that emphasise on the central role that a data-driven culture has on the emergence of radical process innovation capabilities. In these studies a reliance on evidence-based decision-making and a culture that supports it are reported as being key for developing a radical process innovation capability (Recker, 2015; Schmiedel et al., 2013; Trkman et al., 2010). The main argument is that managers should guide a process of cultural change so that the use of BDA and intelligence are promoted, and evidence-based decision-making becomes ingrained in the way the business operates (Popovič et al., 2009). Hence, BDA may not necessarily produce gains in terms of radical process innovation capabilities *per se*, but the culture that is developed and how people view the value of information can promote such outcomes (Brook & Pagnanelli, 2014; Park et al., 2017). In alignment with past research, we find that developing a strong radical process innovation capability is strongly dependent on management skills, and the ability of management to propel a shared culture (Kim et al., 2012). This can also explain to some extent why in Solutions 3a and 3b that correspond to SMEs, formal organisational learning practices either have a peripheral or no importance. Prior studies have found that for the SME size-class, a radical innovation orientation typically falls on the shoulders of managers. This is mainly due to a lack of formalised learning processes (Salavou & Lioukas, 2003).

Adding to the above, the outcomes demonstrate how much contextual factors influence the core and peripheral elements in achieving both incremental and radical process innovation capabilities. There has been a growing body of research within the business process management literature that highlights the roles of adopting a contingency theory perspective to determine the conditioning effects that such aspects may have on outcomes (Niehaves et al., 2014; Trkman, 2010; Vom Brocke et al., 2016). Yet, such contextual and contingency factors are seldom investigated in quantitative studies with regards to process innovation (Trkman, 2010). While such approaches have in the past been examined through hypothetical examples (J. Vom Brocke et al., 2016), our analyses demonstrate how they can be investigated using quantitative data using fsQCA. In this study, we build on past literature which argues that a competitive environment could act as an instigator of developing an innovation culture to survive in such conditions (Maes & Sels, 2014). This position has been also advocated in business process management literature, where it is suggested that firms should build additional capacities and competencies focusing on change and risk management (Borch & Batalden, 2015), and that firms must align their internal structure and strategy in relation to the external environment (Rogers et al., 1999). Our results confirm this assumption, as in all solutions there is at least one form of environmental uncertainty, indicating that the environment can prompt the move towards developing process innovation. When comparing the findings between high and very high levels of process innovation capabilities, we observe that the top-performing firms are those that have adopted a more consonant approach and have managed to invest in a broader range of resources to leverage their big data investments. In other words, instead of relying on a single mechanism to drive innovation, very highly performing firms utilise both individuals as well as organisational resources to sustain superior process innovation capabilities.

5.2. Practical implications

From a practical point of view, the outcomes suggest that managers should develop different strategies in relation to their BDA initiatives. Doing so depends greatly on the types of business process innovation they aim to achieve. Furthermore, such plans should also take into account the contingencies of the environment and the organisation. Specifically, our results suggest that when it comes to radical process innovation capabilities in the service industry, data governance practices should encourage the breakdown of organisational silos and promote the notion of data-driven decision-making at all levels of the organisation (Mikalef et al., 2018c). Nevertheless, this is not a requirement if firms operate in product-based industries that are heterogeneous and hostile. In addition, managerial knowledge on data-driven initiatives and the potential application of big data to organisational 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. In academic literature and popular press, there still seems to be a trend towards one-size-fits-all, where enablers and hindrances are treated the same regardless of what firms try to achieve with BDA and irrespective of what industry and conditions they operate in. This could well be one of the reasons why many BDA initiatives still fail to realise business value. There is some debate whether it is necessary for firms to adopt a uniform strategy when investing in big data resources or if some aspects should be prioritised. Our outcomes demonstrate that the latter is the case; however, it may even be that for some firms investing in novel technological developments like BDA, such investments can constitute a burden rather than a solution. This leads us to the limitations of the current study and a description of ways which future research can continue this work.

5.3. Limitations and future research

While the results of this study shed some light on the relationship of BDA resources and process innovation capabilities, this work unavoidably has some 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 BDA is applied are likely to yield different results and may 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 explained. A complementary study adopting a qualitative approach would likely reveal more insight on how value is produced from such investments through a process perspective. Fourth, while fsQCA is a good way of producing configurations of elements that lead to a specific outcome, one of the limitations of the method is that it is sensitive to frequency cut-off and consistency thresholds, which are manually set by the researcher (Byrne & Ragin, 2009). Adding to this, fsQCA develops solutions based on specific thresholds of outcomes and by defining outcomes in terms of clear and specific indicators, while cluster analysis has the benefit of findings constellations of cases without the need of determining a specific dependent variable. This difference in methodologies also is closely tied with the styles and types of theorisations that are developed (Delbridge & Fiss, 2013). Finally, one of the limitations of the study concerns the choice of research method. Ideally, it would have been preferable to benchmark outcomes in relation to objective measures. Nevertheless, we had to rely on subjective data since the indicators used to measure their success are dependent upon the context in which they are applied.

Disclosure Statement

No potential conflict of interest was reported by the authors.

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Appendix A. Survey Instrument

Measure	Item	Mean	S.D.
Big data analytics capability			
Tangible			
• Data	D1. We have access to very large, unstructured, or fast-moving data for analysis	4.91	1.74
	D2. We integrate data from multiple sources into a data warehouse for easy access	5.05	1.76
	D3. We integrate external data with internal to facilitate analysis of our business environment	4.01	1.80
• Basic resources	BR1. Our "big data analytics" projects are adequately funded	4.13	1.77
	BR2. Our "big data analytics" projects are given enough time to achieve their objectives	4.01	1.62
• Technology	T1. We have explored or adopted parallel computing approaches (e.g., Hadoop) to big data processing	3.69	2.12
	T2. We have explored or adopted different data visualisation tools	4.81	1.85
	T3. We have explored or adopted new forms of databases such as Not Only SQL(NoSQL)	4.17	2.13
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.	4.40	1.65
	MS2. Our BDA managers are able to coordinate big data-related activities in ways that support other functional managers, suppliers, and customers	4.18	1.63
	MS3. Our BDA' managers are able to understand and evaluate the output extracted from big data	4.52	1.58
• Technical skills	TS1. Our "big data analytics" staff has the right skills to accomplish their jobs successfully	4.24	1.70
	TS2. Our "big data analytics" staff is well trained	4.24	1.71
Intangible			
• Data-driven culture	DD1. We base our decisions on data rather than on instinct	4.39	1.47
	DD2. We are willing to override our own intuition when data contradict our viewpoints	4.51	1.52
	DD3. We continuously coach our employees to make decisions based on data	4.37	1.46
• Organisational learning	OL1. We are able to acquire new and relevant knowledge	5.02	1.29
	OL2. We have made concerted efforts for the exploitation of existing competencies and exploration of new knowledge	4.51	1.41
Environmental uncertainty			
Dynamism	DYN1. Products and services in our industry become obsolete very quickly	4.07	1.22
	DYN2. The product/services technologies in our industry change very quickly	4.13	1.35
	DYN3 We can predict what our competitors are going to do next (Reverse coded)	3.74	1.22
	DYN4. We can predict when our products/services demand changes (Reverse coded)	3.95	1.45
Heterogeneity	In our industry, there is considerable diversity in:		
	HET1. Customer buying habits	3.89	1.23
	HET2. Nature of competition	4.01	1.54
	HET3. Product lines	3.92	1.23
Hostility	The survival of this organisation is currently threatened by:		
	HOST1. Scarce supply of labour	3.99	1.52
	HOST2. Scarce supply of materials	3.92	1.39
	HOST3. Tough price competition	4.10	1.40
	HOST4. Tough competition in product/service quality	4.08	1.36
	HOST5. Tough competition in product/service differentiation	4.01	1.38
Innovative capability	How would you rate your organisations capability to generate the following types of innovations in the processes you introduce		
Incremental	INC1. Innovations that reinforce our prevailing product/service lines	4.52	1.36
	INC2. Innovations that reinforce our existing expertise in prevailing products/services	4.39	1.23
	INC3. Innovations that reinforce how you currently compete	4.38	1.31
Radical	RAD1. Innovations that make our prevailing product/service lines obsolete	4.28	1.30
	RAD2. Innovations that fundamentally change our prevailing products/services	4.19	1.38
	RAD3. Innovations that make our expertise in prevailing products/services obsolete	4.27	1.38

Appendix B. Cross-loadings

	D	BR	T	MS	TS	DD	OL	DYN	HET	HOS	INC	RAD
D1	**0.714**	0.199	0.480	0.286	0.294	0.156	0.270	0.254	0.258	0.105	0.219	0.288
D2	**0.725**	0.238	0.224	0.402	0.439	0.278	0.308	0.187	0.335	0.343	0.171	0.192
D3	**0.817**	0.216	0.457	0.543	0.360	0.206	0.541	0.267	0.276	0.330	0.083	0.265
BR1	0.272	**0.946**	0.249	0.387	0.520	0.260	0.352	0.362	0.315	0.326	0.337	0.401
BR2	0.242	**0.842**	0.172	0.387	0.312	0.343	0.296	0.306	0.237	0.353	0.307	0.378
T1	0.408	0.227	**0.826**	0.290	0.245	0.051	0.269	0.106	0.220	0.136	0.079	0.217
T2	0.495	0.202	**0.795**	0.303	0.308	0.267	0.338	0.310	0.208	0.169	0.126	0.348
T3	0.489	0.180	**0.859**	0.318	0.198	0.181	0.326	0.267	0.205	0.211	0.091	0.275
MS1	0.460	0.317	0.335	**0.837**	0.425	0.286	0.524	0.328	0.372	0.388	0.163	0.191
MS2	0.517	0.419	0.334	**0.918**	0.569	0.231	0.437	0.189	0.368	0.365	0.253	0.323
MS3	0.494	0.379	0.303	**0.869**	0.512	0.295	0.396	0.244	0.413	0.411	0.191	0.369
TS1	0.436	0.435	0.298	0.527	**0.945**	0.335	0.340	0.225	0.337	0.329	0.176	0.280
TS2	0.454	0.487	0.284	0.564	**0.949**	0.315	0.373	0.201	0.251	0.430	0.283	0.376
DD1	0.238	0.133	0.152	0.240	0.201	**0.823**	0.270	0.253	0.294	0.334	0.217	0.370
DD2	0.128	0.250	0.109	0.144	0.214	**0.793**	0.285	0.355	0.180	0.225	0.284	0.233
DD3	0.285	0.394	0.273	0.357	0.412	**0.818**	0.312	0.327	0.204	0.294	0.246	0.353
OL1	0.541	0.235	0.379	0.489	0.338	0.293	**0.880**	0.313	0.452	0.305	0.171	0.373
OL2	0.398	0.407	0.303	0.421	0.329	0.337	**0.891**	0.300	0.297	0.328	0.150	0.269
DYN1	0.374	0.392	0.372	0.433	0.027	0.230	0.208	**0.801**	0.380	0.391	0.143	0.179
DYN2	0.265	0.303	0.456	0.312	0.110	0.143	0.179	**0.824**	0.292	0.260	0.142	0.169
DYN3	0.215	0.165	0.305	0.268	0.030	0.142	0.169	**0.834**	0.287	0.255	0.114	0.116
DYN4	0.176	0.366	0.347	0.316	0.228	0.114	0.116	**0.802**	0.370	0.280	0.263	0.200
HET1	0.382	0.290	0.286	0.428	0.309	0.340	0.465	0.496	**0.872**	0.517	0.254	0.345
HET2	0.251	0.316	0.181	0.372	0.237	0.197	0.266	0.332	**0.839**	0.345	0.240	0.467
HET3	0.292	0.260	0.116	0.429	0.313	0.257	0.321	0.473	**0.831**	0.269	0.321	0.404
HOS1	0.287	0.255	0.069	0.373	0.347	0.351	0.337	0.518	0.464	**0.921**	0.289	0.410
HOS2	0.370	0.280	0.113	0.402	0.430	0.343	0.315	0.487	0.451	**0.934**	0.307	0.350
HOS3	0.396	0.176	0.385	0.316	0.351	0.387	0.204	0.306	0.322	**0.864**	0.353	0.374
HOS4	0.426	0.207	0.338	0.250	0.367	0.247	0.196	0.425	0.307	**0.892**	0.417	0.356
HOS5	0.372	0.433	0.374	0.229	0.435	0.336	0.184	0.126	0.178	**0.887**	0.322	0.311
INC1	0.119	0.410	0.027	0.230	0.208	0.343	0.263	0.231	0.164	0.354	**0.815**	0.439
INC2	0.287	0.116	0.110	0.143	0.179	0.125	0.196	0.425	0.307	0.125	**0.783**	0.348
INC3	0.087	0.263	0.030	0.142	0.169	0.240	0.188	0.439	0.108	0.257	**0.753**	0.345
RAD1	0.126	0.132	0.228	0.114	0.116	0.082	0.119	0.396	0.176	0.144	0.321	**0.764**
RAD2	0.314	0.214	0.246	0.263	0.200	0.338	0.207	0.426	0.555	0.278	0.361	**0.787**
RAD3	0.279	0.441	0.306	0.254	0.345	0.374	0.392	0.372	0.433	0.393	0.439	**0.890**

D – Data, BR – Basic Resources, T – Technology, MS – Managerial Skills, TS – Technical Skills, DD – Data-driven Culture, OL – Organisational Learning, DYN – Dynamism, HET – Heterogeneity, HOS – Hostility, INC – Incremental Process Innovation Capability, RAD – Radical Process Innovation Capability

Appendix C. Heterotrait-Monotrait Ratio (HMTM)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Managerial skills									
(2) Technical skills	0.662								
(3) Data-driven culture	0.387	0.420							
(4) Organisational Learning	0.661	0.470	0.486						
(5) Dynamism	0.421	0.303	0.213	0.285					
(6) Heterogeneity	0.462	0.324	0.411	0.346	0.412				
(7) Hostility	0.405	0.324	0.297	0.373	0.563	0.561			
(8) Incremental process innovation capabilities	0.234	0.368	0.395	0.342	0.504	0.533	0.507		
(9) Radical process innovation capabilities	0.311	0.395	0.465	0.428	0.415	0.452	0.436	0.561	

Appendix D. Sub-sample configurations of high process innovation capabilities

Intermediate models for sub-sample 1		Raw coverage	Unique coverage	Consistency
Incremental process innovation capabilities				
1.	D*T*~BR*TS*~MS*~DD*~DYN*HET*~HOS*LF*PI	0.28	0.24	0.91
2.	D*T*BR*TS*MS*DYN*~HET*~LF*SI	0.21	0.14	0.92
3.	D*BR*TS*~MS*DD*OL*DYN*~HOS*~LF*SI	0.21	0.11	0.92
4.	D*T*BR*TS*MS*DYN*HET*LF*SI	0.16	0.16	0.94
Overall solution consistency: 0.89				
Overall solution coverage: 0.39				
Radical process innovation capabilities				
1.	D*T*BR*TS*MS*~DD*~OL*~DYN*HET*HOS *LF*PI	0.23	0.20	0.88
2.	D*BR*MS*DD*OL*DYN*~HET*HOS *LF*SI	0.17	0.14	0.91
3.	D*T*TS*MS*DD*DYN*~HET*~HOS*LF*SI	0.14	0.12	0.87
4.	D*TS*MS*DD*OL*DYN*HOS*LF*SI	0.15	0.13	0.87
Overall solution consistency: 0.87				
Overall solution coverage: 0.36				

D – Data, BR – Basic Resources, T – Technology, MS – Managerial Skills, TS – Technical Skills, DD – Data-driven Culture, OL – Organisational Learning, DYN – Dynamism, HET – Heterogeneity, HOS – Hostility, LF – Large Firms, SME – Small-Medium Enterprises, PI – Product Industry, SI – Service Industry

Appendix E. Truth Tables for Incremental and Radical Process Innovation Capabilities

Tables E1 and E2 present the truth tables for incremental and radical process innovation capabilities, accordingly. The minimum acceptable frequency of cases was set at three, which is depicted in the "number" columns. As a result, we only consider combinations of factors with at least three empirical occurrences for further analysis. Due to a limitation of space, we do not depict instances with less than three occurrences in the following tables. The truth table algorithm calculates a consistency score that explains how reliably a combination results in the given outcome. To verify that outcomes and solutions are reliable, we use both raw consistency, and proportional reduction in inconsistency (PRI) as measures for gauging consistency levels. We retained rows (i.e., combinations of conditions) that satisfy the frequency threshold and have at least 0.80 raw consistency, and a minimum threshold of 0.75 of PRI consistency. Having extracted the truth tables, the next step in the analysis was running the truth table algorithm to reduce the number of combinations into a smaller set of configurations based on the fuzzy-set algorithm and counterfactual analysis.

Table E1. Truth table for incremental process innovation capability.

DT	TCH	BR	TS	MS	OL	DD	DYN	HET	HOS	LAR	SME	PR	SI	Number	INC	Raw Consistency	PRI Consistency
1	1	1	1	0	0	0	0	1	1	1	0	1	0	16	1	0.91	0.90
1	1	0	1	0	1	0	0	1	0	1	0	1	0	9	1	0.89	0.87
1	1	1	1	1	0	0	1	0	1	0	1	0	1	8	1	0.93	0.90
1	0	1	1	0	1	1	1	0	0	0	1	0	1	7	1	0.90	0.87
1	1	1	1	0	0	0	1	1	0	1	0	0	1	7	1	0.89	0.85
1	1	0	1	1	1	1	1	1	0	1	0	1	0	4	1	0.94	0.91
1	0	1	1	0	1	1	1	1	0	1	0	0	1	3	1	0.96	0.95
1	1	1	1	1	1	0	1	1	1	1	0	0	1	3	1	0.97	0.95
1	0	1	1	0	1	1	1	1	1	1	0	0	1	3	1	0.96	0.94
1	0	0	0	1	1	1	1	0	1	0	1	1	0	3	0	0.79	0.73
0	1	1	1	0	1	0	1	0	1	1	0	0	1	3	0	0.78	0.71
1	0	0	0	0	1	0	0	1	0	0	1	1	0	3	0	0.79	0.73
1	0	0	1	1	1	0	1	0	1	1	0	0	1	3	0	0.77	0.72

Table E2. Truth table for radical process innovation capability.

DT	TCH	BR	TS	MS	OL	DD	DYN	HET	HOS	LAR	SME	PR	SI	Number	RAD	Raw Consistency	PRI Consistency
1	1	1	1	1	0	0	0	1	1	1	0	1	0	15	1	0.94	0.93
1	0	0	0	1	1	1	1	0	1	1	0	0	1	13	1	0.91	0.88
1	0	0	1	1	1	1	1	1	1	1	0	1	0	8	1	0.92	0.90
1	1	0	1	1	0	1	1	0	0	0	1	0	1	7	1	0.88	0.86
1	0	0	1	1	1	1	1	1	1	1	0	1	0	5	1	0.92	0.89
1	1	1	1	1	1	1	1	1	1	1	0	0	1	4	1	0.91	0.88
1	0	1	0	1	1	1	1	0	1	1	0	0	1	3	1	0.93	0.90
1	0	0	1	1	1	1	1	0	1	0	1	0	1	3	1	0.88	0.86
1	1	1	1	0	1	0	0	1	1	0	1	1	0	3	0	0.77	0.73
0	1	1	1	0	1	1	1	0	1	0	1	0	1	3	0	0.78	0.74
1	1	0	0	0	1	1	1	0	0	1	0	1	0	3	0	0.76	0.73

Note: DT – Data; TCH – Technology; BR – Basic Resources; TS – Technical Skills; MS – Managerial Skills; OL – Organisational Learning; DD – Data-drive Culture; DYN – Dynamism; HET – Heterogeneity; HOS – Hostility; LAR – Large Firms; SME – Small-Medium Enterprises; PI – Product Industry; SI – Service Industry; INC – Incremental Process Innovation Capability; RAD – Radical Process Innovation Capability