Achieving Strategic Flexibility in the Era of Big Data: The Importance of Knowledge Management and Ambidexterity

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Abstract

Purpose – This research unpacks the micro-mechanisms that exist between an organisation's ability to conduct Big Data Analytics (BDA) and its achievement of strategic flexibility. Knowledge management capabilities and organisational ambidexterity have long been considered factors influencing the aforementioned relationship. In order to assess this, the authors build on dynamic capabilities as the main theoretical lens through which to examine.

Design/methodology/approach – Structural Equation Modelling (SEM) is the main methodological approach used in this research. A structural model was developed and tested based on 215 survey responses collected from managers of organisations in continental Europe.

Findings – The results indicate that BDA capabilities are a significant antecedent of an organisation's strategic flexibility. This relationship, however, is influenced by knowledge management capabilities and ambidexterity.

Practical implications – Managers wishing to properly exploit the potential of big data should invest in the elaboration of knowledge management processes across their organisation. This strategy can foster strategic flexibility.

Originality/value – Previous research has explored the theoretical links between big data, knowledge management, and strategic flexibility. However, little attention has been paid to the quantitative investigation of the phenomenon.

Keywords – Big data; BDA capabilities; Knowledge management; Ambidexterity; Strategic flexibility.

Paper Type – Research Paper

1. Introduction

Big data has been at the forefront of recent discussions concerning management (Dubey *et al.*, 2018; Lombardi, 2019). O' Leary (2013) defines 'big data' as an extremely large amount of structured and unstructured data, available immediately everywhere which, due to its intricacies, cannot be managed using traditional methods. Big data differs from typical database files as it is characterized by different *Volume*, *Velocity*, *Variety*, *Veracity*, *Value*, *Variability* and *Visualization* (a.k.a. the seven 'V's). These data types are unstructured and they present challenges in terms of their dimensions, the speed with which they are generated and should be acted upon, the different formats of individual files (i.e. photos, text, tables, video, etc.), and their potential to contain visually valuable insights (Wamba *et al.*, 2017). As a result of the magnitude of information contained, big data allows managers to make decisions building on real-facts rather than intuition (McAfee and Brynjolfsson, 2012; Ferraris *et al.*, 2019) and, consequently, the availability of big data has been linked to improved organisational performance (Rialti *et al.*, 2018).

To fully leverage the strategic potential of big data, modern businesses need big data analytics (BDA). BDA has been seen to have a tremendous impact on organisations (Wamba *et al.*, 2017) as, through BDA, managers can monitor the use of data, processes, possible bottlenecks in workflow, and employees' performance (Akter *et al.*, 2016). Competitors can be monitored using technology to ascertain their levels of operation and performance (Erevelles *et al.*, 2016). Finally, customers' behavioural patterns can also be investigated in real-time, both on individual and aggregate levels (Hofacker *et al.*, 2016). BDA thus comprises an ensemble of powerful computational techniques in order to uncover trends and establish patterns within and between these particularly large socio-economic datasets (Labrinidis and Jagadish, 2012; George *et al.*, 2014). These analytical tools can then assist organisations (depending on the types of information at their disposal) to navigate, manoeuvre, compete with, and adapt to the ever-changing business environment (Wamba *et al.*, 2017). In short, thanks to the availability of big data and BDA, organisations are able to achieve a higher level of dynamism and reactivity in terms of change. As such, BDA has been associated with enhanced ambidexterity, agility, dynamic capabilities, and market responsiveness (Rialti *et al.*, 2019a).

Despite the growing number of studies analysing BDA, scarce attention has been paid by researchers to the links between BDA and strategic flexibility. Specifically, existing academic literature neglects to explore the organisational micro-mechanisms that have facilitated the transformation of these new tools and capabilities into new organisational capacities, allowing a company to react to new situations. Similarly, with the exception of a few recent studies (i.e. Ferraris *et al.*, 2019; Rialti *et al.*, 2019a; b), scarce attention has been paid to the importance of knowledge management practices in the era of big data. Building on dynamic capabilities, this paper will empirically investigate the ways in which BDA capabilities serve to influence organisational flexibility. In doing so, we posit that knowledge management capabilities and organisations' ambidexterity are two factors that serve to influence the aforementioned relationship. Data from a survey distributed to 215 managers of large continental European companies were analysed to test a Structural Equation Model (SEM) developed according to existing literature. Our findings show that BDA capabilities can be considered significant antecedents of strategic flexibility and that knowledge management capabilities and ambidexterity influence this relationship. This paper contributes to both theory and practice in the fields of knowledge management and strategic management. In particular, our findings reveal the ways in which the successful use of BDA derives from existing knowledge management capabilities which enhance an organisation's ability to identify new opportunities and to subsequently exploit them.

The paper is structured as follows. The second section outlines the theoretical background of BDA capabilities, paving the way for the development of hypotheses building upon this model. The third section focuses on the sampling procedure and the preliminary analyses that have been performed. The fourth section outlines our methodology and, finally, in the fifth and the sixth sections, results are discussed and conclusions are drawn.

2. Theoretical background

Modern organisations should develop a set of capabilities to allow them to fully take advantage of the insights that could be provided by big data. Recent studies (Wamba *et al.*, 2017) have identified the ways in which these capabilities can be categorised into BDA managerial capabilities, BDA personnel capabilities, and BDA infrastructure flexibility. BDA managerial capabilities are essential when choosing and executing the right BDA infrastructure and when harvesting information from the datasets. The decision-maker must hold certain skills in order to determine a technical solution and understand the information extracted (Provost and Fawcett, 2013). BDA personnel are further down in the hierarchy but are essential within an organisation. Employees with the requisite skills can identify the right data, analyse this data, and maintain the integrity of the company's infrastructure (Wamba *et al.*, 2017). BDA personnel capabilities emerge directly from the existing skills of data analysts, scientists, and architects dealing with datasets and technological infrastructures (De Mauro *et al.*, 2018). BDA infrastructures include all technical information systems capable of collecting, storing, processing, and analysing rigid or non-self-adaptable big data to different kinds of data, which are fundamental in facilitating the flow of data in any situation (Wamba *et al.*, 2017). When it comes to infrastructural flexibility, this means that these infrastructures should not only be capable of ensuring the analysis of data but should also be able to handle increasing volumes of data (Wang *et al.*, 2018). According to pertinent academic literature in this field, organisations have previously struggled to decode large datasets using traditional data-mining techniques (Labrinidis and Jagadish, 2012). The effective use of big data analytics (BDA) capabilities is now essential in enabling organisations to dispense data formats in a timely manner, whilst simultaneously allowing management to decodify and transform data in order to make decisions that enhance organisational performance (Vera-Baquero *et al.*, 2016). For example, the influence of BDA capabilities can be observed in the revolutionization of supply-chain management (Wang *et al.*, 2016) and marketing in terms of strategic development (Erevelles *et al*., 2016). Nevertheless, previous research has neglected to focus on the empirical investigation of the impact of BDA capabilities on ambidexterity (observed as exploitative innovation and explorative innovation) and flexibility.

2.1 BDA Capabilities and Ambidexterity

Organisations able to successfully survive in a turbulent environment do so by compartmentalising their structure into explorative and exploitative divisions, thus making themselves ambidextrous (O'Reilly and Tushman, 2008). These companies often have decentralised structures and a common culture and vision (O'Reilly and Tushman, 2013) and ambidextrous organisations are typically able to explore their environment and exploit emerging opportunities. 'Exploration' here refers to an organisation's propensity to investigate, take chances, uncover, and explore new methods in order to prepare to exploit their particular field. 'Exploitation' refers to an organisation's ability to implement modernisation, construct, enhance, and successfully complete objectives (Gibson and Birkinshaw, 2004; Rialti, *et al.*, 2018). Ambidextrous organisations, then, can quickly respond to market changes, whilst meeting and maintaining an adequate satisfaction level among their existing consumers (Lubatkin *et al.*, 2006). Information is therefore critical to achieving ambidexterity and, when information is directed to the right person within an organisation, an organisation can transform itself by taking more initiative and better identifying and exploiting opportunities (Wamba *et al.*, 2017).

The importance of this phenomenon has been widely recognized in scholarly literature, both in studies concerning the ways in which management information systems are vital to ambidextrous organisations (Bresciani *et al*., 2017), and in recent literature analysing the effect of BDA on organisations (Rialti *et al.*, 2019; Shams and Solima, 2019). The primary objective of collecting and analysing big data is indeed to advance practical acumens and gain new knowledge in order to establish competitive advantages (Ferraris *et al*., 2019). Hence, BDA is relevant in that it allows managers to understand, extract, and generate useful information and knowledge (Chen *et al*., 2012;

Ferraris *et al*., 2019) which, through interpretation and categorisation, can lead to effective management during environmental transitions (Ferraris *et al*., 2019). The emergence of big data has, without a doubt, revolutionised the features and capabilities of information systems (Yin and Kaynak, 2015), to the point where BDA infrastructures can now continuously monitor processes and provide targeted information to management. Therefore, organisations should invest in personnel, managerial, and internal technical capabilities in order to fully leverage the potentialities that big data and BDA can offer (Akter *et al*., 2016; Rialti *et al.*, 2019).

This notion has been confirmed in existing academic research on BDA capabilities and the organisation's dynamic capabilities. These studies have stressed that BDA capabilities are dynamic capabilities and that they can enable an organisation to benefit from a greater amount of information. Specifically, the ability to extract information from unstructured datasets has been considered a fundamental capability for any organisation wishing to implement routines that may increase its flexibility and its propensity to succeed in times of difficulty (Chierici *et al.*, 2019).

As such, BDA capabilities have been shown to be integral to the pursuit of ambidexterity in that they are related to organisations' dynamic capabilities, which are a critical antecedent of ambidexterity (Wamba *et al.*, 2017). This information could increase an organisation's ability to identify and exploit new opportunities emerging in the environment. Thus, we hypothesize:

H1: *BDA capabilities are positively related to explorative innovation*.
H2: *BDA capabilities are positively related to exploitative innovation*.

2.2 The role of knowledge management

Knowledge has been defined as a justified belief that is organised and established and seeks to improve an organisation's performance through effective and efficient action (Nonaka, 1994; Ferraris *et al.*, 2019). Thanks to knowledge management capabilities, modern organisations can develop an "absorptive capacity": the ability to use previously obtained information in order to identify and perceive the value of new information, understand it, and utilise it in order to formulate new knowledge (Cohen and Levinthal, 1990; Gold *et al.*, 2001). New knowledge is usually created by combining existing knowledge with new knowledge and exchanging information, both of which necessitate social capital. Here, social capital is the collection of existing and possible resources embedded in a given social unit's relationship networks (Nahapiet and Ghoshal, 1998; Gold *et al.*, 2001).

Knowledge management involves three processes: acquisition, conversion, and application (Gasik, 2011; Gold *et al*., 2001; Ferraris *et al.*, 2019). The acquisition is the method used to extrapolate new knowledge from existing data and information. Conversion is the process of making the knowledge obtained beneficial to the company. Knowledge application (tacit and explicit) is the use of this knowledge to accomplish a task. Marketing practitioners operate in this way, capturing structured and unstructured information about consumers' daily behaviour in order to fully exploit this knowledge (O'Connor and Kelly, 2017). Therefore, knowledge management is an organisation's processes of obtaining and converting knowledge into an arrangement that is easily usable, accessible, and applicable to the organisation. When information is not distributed within the organisation via the appropriate knowledge channels, it is unlikely to reach the relevant employees within the organisation through which it would be rendered useful.

Effective knowledge management uses technological scopes, including business intelligence-distributed learning, uncovering new sources of information, mapping new information, knowledge application, the cultivation of opportunities, and knowledge security (Gold *et al.*, 2001). Through this, business intelligence is shown to be a useful tool in allowing an organisation to produce knowledge about its rivals and its general business environment. Collaboration and distributed learning allow employees within a company to cooperate and learn from each other. This helps to reduce/remove barriers in operations and locations that have previously been characterised by these obstacles. Organisations must ensure that the knowledge acquired is carefully guided in such a way that is not stolen or used incorrectly (O'Connor and Kelly, 2017).

Proper information systems and information management capabilities, as previous scholarly literature has observed, are fundamental in facilitating knowledge management. Indeed, these systems and capabilities can influence the ways in which data is collected, how knowledge is able to flow thought an organisation, and the methods by which new knowledge is created. Therefore, BDA capabilities are fundamental in turning data into information that can be transformed into usable knowledge. There have been many discussions concerning the interdependency between BDA and knowledge management (Gold *et al.*, 2001). BDA and knowledge management support each other by sharing their common knowledge of business intelligence along with human knowledge, which helps to improve organisational performance in various ways. Organisations can then share information and data with different stakeholders (Nickerson and Zenger, 2004; Xu *et al.*, 2016), direct specific knowledge in a timely manner, and transform information on customers and other organisations into valuable insights. BDA can, for instance, through search engines, search analytics, web analytics, customer analytics, and pay-per-click management, be used to obtain computerised and personalised knowledge (Xu *et al.*, 2016). This could help the whole organisation to refine its information, allowing these insights to reach the right person, thus increasing the effectiveness of the organisation's BDA capabilities. Therefore, we hypothesize:

H3: *BDA capabilities are positively related to an organisation's knowledge management orientation.*

Effective knowledge management is related to the ways in which employees deal with information. In this way, employees within an organisation should not only know their trade, but they should also be able to interpret and respond to information to ensure the long-term survival of the business. However, competitive pressure, a rapidly evolving environment, and a short product life span are some of the issues that necessitate an organisation's use of both exploration and exploitation in order to thrive and reach better performance levels (O'Reilly and Tushman, 2008; Raish and Birkshinshaw, 2008). Exploration concerned with experimentation and exploitation denotes the refinement and expansion of existing competencies, technologies, and archetypes (Filippini *et al*., 2012). Organisations need to optimise their modes of developing exploitation and exploration. This can help them to be more effective in the short term and be more innovative in the long run (Levinthal and March, 1993). Creating harmony and balance in both modes of learning is difficult but possible. This is consistent with the research of other scholars (Raisch *et al.*, 2009; Filippini *et al.*, 2012), who argue that ambidextrous companies are capable of exploiting the competencies that they already possess and assessing new opportunities at the same time. The purpose of each concept (exploitation and exploration) is as follows: exploitation uses existing knowledge efficiently, even though innovation is important; while exploration enables knowledge sharing, which facilitates the development of new approaches (Swan *et al*., 1999). Therefore, exploratory innovation is the cultivation and commercialisation of new services or products, while exploitative innovation is concerned with facilitating advances in processes and technologies in order to develop existing products and services offered (Ko and Liu, 2016). Similarly, knowledge management is positively associated with the pursuit of innovation and, while investment in the growth of new knowledge can push organisations towards different business ventures and appealing markets, innovation can be combined with competitive orientation. The resultant movement is dependent on the knowledge of individuals and the company's technological base. It is impossible to innovate without new knowledge regarding customers, competitors, and business environments. From this knowledge, new ideas (related to explorative innovation) emerge. For exploitative innovation, knowledge instead allows organisations to better understand which opportunities are favourable. Thus, we hypothesize:

H4: *The knowledge management capabilities of an organisation are positively related to its*

explorative innovation capabilities.
H5: *The knowledge management capabilities of an organisation are positively related to its capacity for exploitative innovation.*

2.3 Ambidexterity and strategic flexibility

There is a general consensus in organisational literature that ambidextrous organisations are successful and are able to adapt to fluctuations in their environment (Raisch and Birkinshaw, 2008), and that strategic flexibility underscores the changeable nature of their resources in establishing a competitive advantage in the shifting marketplace (Zhou and Wu, 2010). According to Wei *et al.* (2014), resource and co-ordination flexibility are the main components of overall flexibility. Resource flexibility denotes an organisation's ability to acquire resources with manifold uses, whereas coordination flexibility is the organisation's propensity to generate innovative combinations of resources through internal coordination procedures. Therefore, an organisation's capacity to accumulate technological capabilities can be linked to its processes of explorative innovation, while exploitation at an increasing rate is linked to advanced exploitative activities (Gibson and Birkinshaw, 2004).

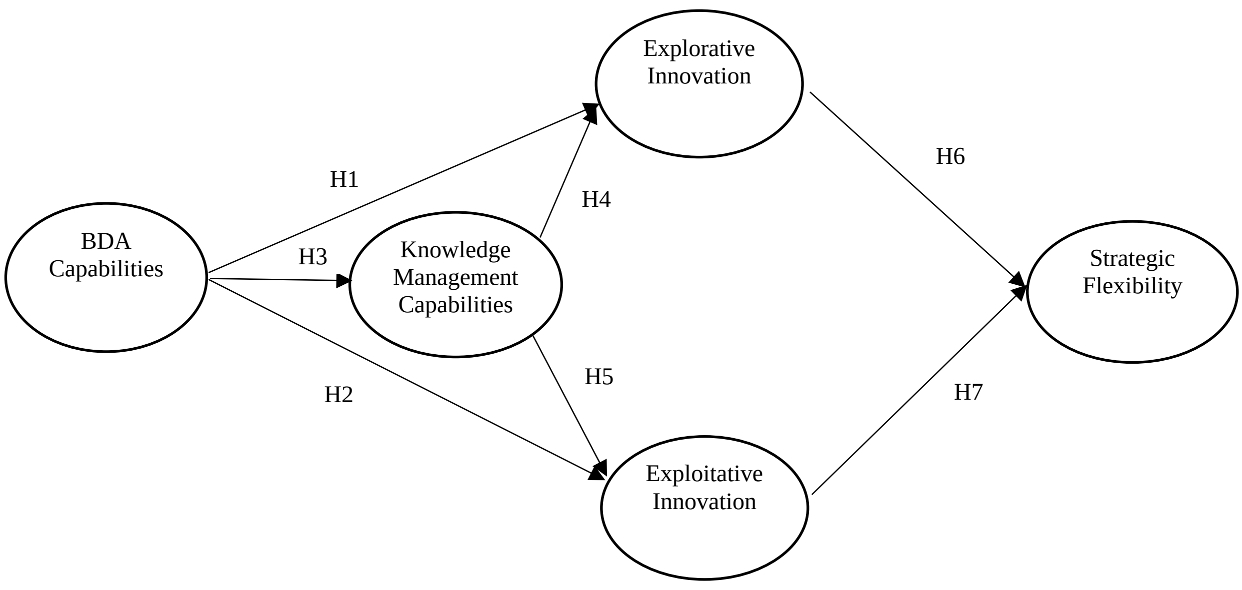
Research on organisational ambidexterity shows that strategic flexibility can stem from an organisation's ability to identify important changes in its external environment, allowing it to either use resources as a result of these changes, or to stop and reverse existing resource commitment. Thus, strategic flexibility cam stems from ambidexterity (Raisch and Birkinshaw, 2008; Wei *et al.*, 2014). The significance of ambidexterity is thus dependant on its positive impact on many performance variables, along with the organisation's ability to survive in an unpredictable environment (O'Reilly and Tushman, 2013; Rojo *et al.*, 2016) An ambidextrous organisation is, therefore, more capable of adapting and reacting to changes. Thus, we hypothesize:

H6: *Explorative innovation is positively related to the achievement of strategic flexibility.*
H7: *Exploitative innovation is positively related to the achievement of strategic flexibility*.

2.4 Proposed Model

Building on the previous hypotheses, the authors have jointly developed the following structural model (see Figure 1). From this perspective, this research attempts to address a significant literature gap, which is represented by the need for the quantitative exploration of the relationship between BDA capabilities, knowledge management capabilities, ambidexterity (in the form of explorative innovation and exploitative innovation), and strategic flexibility (Lu and Ramamurthy, 2011; Dubey *et al.*, 2018).

Figure 1. Proposed Model



Source: Authors' elaboration

3. Research Methodology

3.1 Sampling

To answer the identified research question, a survey was administered to a sample of managers employed by continental European organisations engaged in BDA-related initiatives. In line with existing research, the authors focused on mostly on big organisations, as these are often the only types of the organisation able to collect enough data to be classified as big data. They are also capable of managing the investments required to develop BDA capabilities (De Mauro *et al.*, 2018). In order to obtain data directly from managers, the responses were collected by a market research company on behalf of the authors. The use of a market research company has been recommended previously in existing research in the business and management sector, wherein researchers seek to contact managers directly without any interference from other employees (Palan and Schitter, 2018). The selected companies formed a subject-pool consisting of more than 20,000 UK, EU, and US managers. Of these, approximately 8,500 were based in continental Europe and held critical roles in their organisations (according to the EU definition of a big enterprise/organisation). Additional screening criteria were considered to extrapolate the final group of perspective respondents. Specifically, the potential respondents were outlined according to their (1) employment status, (2) role within the organisation, (3) expertise concerning big data, and (4) industry.

A total of 215 completed and usable surveys out of 730 were returned. A response rate of 29.45% was achieved. In line with previous research targeting managers (Baruch and Holtom, 2008), 145 respondents were men (67.4%) and 70 were women (32.6%). Most of them held at least a bachelor's degree (51.1%) and had more than 10 years' experience using management information systems (46.9%). Information about the respondents is provided in Table 1.

Table 1. Sample Characteristics

Control Variable	Frequency	Valid Percent
Age		
18-24	12	5.6
25-29	31	14.4
30-39	117	54.5
40+	55	25.5
Education		
High school	56	26.0
Bachelor's degree	110	51.1
Master's degree	40	18.8
PhD	9	4.1
Years of experience		
Less than 1 year	5	2.4
1-5 years	59	27.5
5-10 years	50	23.2
More than 10 years	101	46.9
Industry		
Adult education	3	1.4
Communication	18	8.3
Computer/electronic	23	10.7
Electricity/oil and gas	4	1.9
Finance/insurance	20	9.3
Hotel and tourism	10	4.6
Information/data processing	31	14.4

Manufacturing	16	7.4
Marketing	9	4.2
Retail	17	7.9
Scientific/health services/pharmacy	40	18.6
Other	24	11.3

Source: Authors' elaboration

3.2 Measures

The administered survey consisted of 82 items, 6 of which were control variables. Organisations' BDA capabilities (managerial, personnel, and infrastructural) were measured using a 49-item scale developed by Wamba *et al.* (2017). A 13-item scale, used to measure knowledge management capabilities (observed as the ensemble of knowledge acquisition, knowledge application, and knowledge sharing capabilities), was originally developed by Gold *et al*. (2001). Gold *et al.* (2001) suggested that the item could also be treated as an aggregated construct, and this method was followed. Then, the authors measured explorative and exploitative innovations using the widely known 8 item ambidexterity scale created by Jansen *et al.* (2009). Strategic flexibility, finally, was assessed through the 6-item scale used by Zhou and Wu (2010).

Respondents rated items using a 7-point Likert scale: 1 was labelled as "strongly disagree" and 7 was labelled as "completely agree".

4. Analysis and results

4.1 Means, standard deviations, and scale reliabilities

Table 2 shows all of the means, correlations, and descriptive reliabilities of the variables used in this study. All scales are characterised by good measures of reliability, ranging from 0.776 (connectivity) to 0.919 (control). Following Nunnally's (1978) seminal research, all variables were considered for the successive Structural Equation Modelling (SEM) analysis. The Cronbach α values of all the variables are above the suggested threshold (α = 0.7) and most variables are significantly correlated.

Table 2. Means, standard deviations, and reliabilities

	Mean	*SD*	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*	*15*	*16*
1) Connectivity	*4.11*	*0.31*	*(0.778)*															
2) Compatibility	*4.58*	*0.28*	0.674	*(0.853)*														
3) Modularity	*4.30*	*0.77*	0.665	0.518	*(0.752)*													
4) Planning	*4.71*	*0.07*	0.718	0.656	0.586	*(0.897)*												
5) Decision-making	*4.92*	*0.67*	0.594	0.513	0.623	0.724	*(0.843)*											
6) Coordination	*4.73*	*0.43*	0.544	0.542	0.519	0.656	0.599	*(0.872)*										
7) Control	*4.85*	*0.33*	0.720	0.701	0.665	0.805	0.716	0.746	*(0.919)*									
8) Technical knowledge	*4.88*	*0.59*	0.632	0.528	0.611	0.686	0.680	0.645	0.798	*(0.908)*								
9) Business knowledge	*5.00*	*0.45*	0.532	0.581	0.526	0.693	0.650	0.655	0.749	0.757	*(0.918)*							
10) Relational knowledge	*4.78*	*0.68*	0.577	0.594	0.556	0.701	0.654	0.661	0.745	0.717	0.807	*(0.869)*						
11) Explorative innovation	*4.46*	*0.12*	0.575	0.470	0.551	0.647	0.609	0.488	0.623	0.538	0.496	0.535	*(0.814)*					
12) Exploitative innovation	*5.12*	*0.23*	0.526	0.476	0.530	0.695	0.700	0.563	0.688	0.612	0.634	0.656	0.686	*(0.845)*				
13) Knowledge application	*5.02*	*0.02*	0.478	0.527	0.472	0.666	0.591	0.542	0.675	0.609	0.685	0.662	0.545	0.639	*(0.899)*			
14) Knowledge acquisition	*5.01*	*0.03*	0.474	0.452	0.470	0.656	0.607	0.510	0.660	0.617	0.662	0.622	0.537	0.684	0.853	*(0.869)*		
15) Knowledge sharing	*4.72*	*0.53*	0.443	0.447	0.481	0.593	0.521	0.565	0.640	0.538	0.595	0.615	0.439	0.511	0.788	0.726	*(0.839)*	

16) Strategic Flexibility	*4.62*	*0.28*	0.575	0.529	0.588	0.717	0.687	0.675	0.646	0.651	0.732	0.756	0.687	0.668	0.659	0.634	0.649	*(0.901)*

Notes:
Cronbach's α reported on the diagonal.

Source: Authors' elaboration using IBM-SPSS v.22

4.2 Measurement Model

A Structural Equation Modelling (SEM) analysis was conducted in order to investigate the hypotheses proposed (see Figure 2) and analyse the existing relationships between the variables.

Firstly, confirmatory factor analysis was carried out using AMOS v. 22 (Arbuckle, 2013). To predict the parameters and assess the extent to which the proposed hypotheses were valid, the authors used the AMOS maximum likelihood function. From this, a measurement model was built, and authors then assessed the measures used to establish the goodness-of-fit in order to verify its parsimony (Bagozzi and Yi, 1988). In terms of absolute fitting indexes, t-test of $\chi2/df = 2.438$ suggests a reasonable level (Bagozzi and Yi, 1988). Similarly, both the goodness-of-fit index (GFI) (0.997) and the root mean square error of approximation (RMSEA = 0.075) suggest an acceptable model fit (Bentler, 1990). The comparative fit index (CFI), the incremental fit index (IFI), the normed fit index (NFI), and the Tucker-Lewis index (TLI) were also calculated. Following Bentler (1990), all of these indexes confirmed the overall fit of the model (CFI = 0.999; IFI = 0.998; NFI = 0.999; TLI = 0.996).

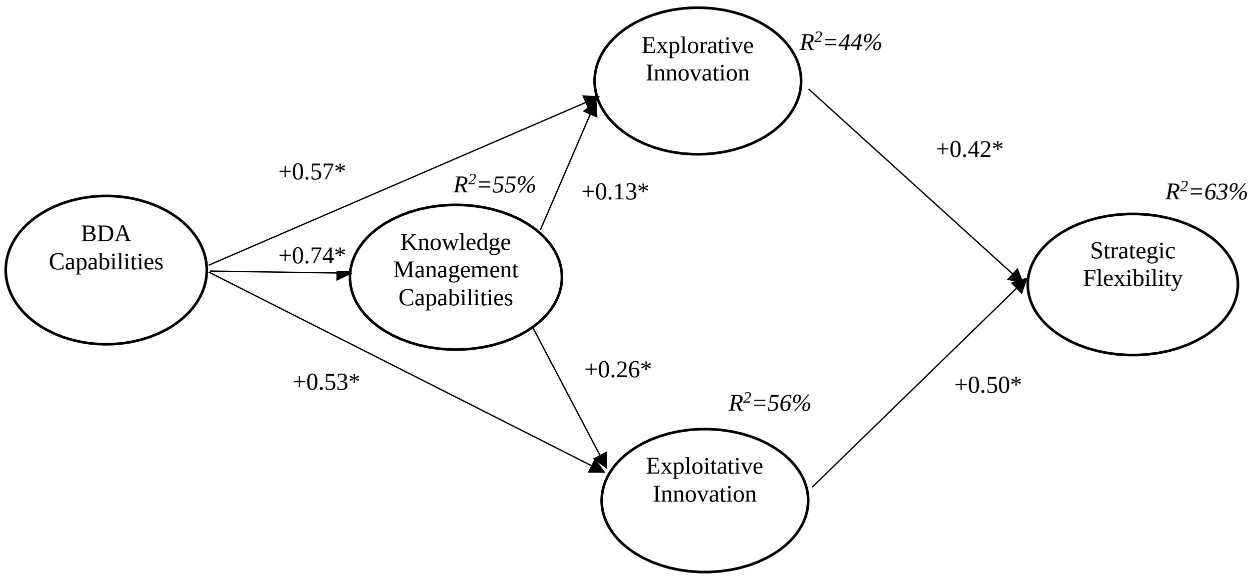
The measurement model also revealed that all factor loadings – the path coefficients between the indicators and the latent variable – were significant ($p < 0.01$). In addition to this, the authors also assessed the internal consistency of indicators by observing the Composite Reliability (CR) of each latent construct. All variables showed that the model had an acceptable CR. Convergent validity was also analysed via the Average of the Variance Extracted (AVE), which estimated the indicators' degree of variability, considering the latent construct (Fornell and Larcker, 1981). AVE values above 0.5, as in our case, indicate reasonable convergent validity (Bagozzi and Yi, 1988). The model was thus deemed acceptable, according to all measures.

The eventual presence of Common Method Bias (CMB) was assessed according to the protocols of Podsakoff *et al.* (2003). The scales were pre-tested in order to remove any potentially unclear items. Next, the authors performed Harman's one-factor test, which failed to establish a particular attribute that accounted for most of the variance. Finally, AMOS confirmatory analysis was used to compare the suggested model with another model which loaded all items into a common method factor: the one-factor model (Podsakoff *et al.*, 2003). As required, the contrast displayed a notable change in $\chi2$. As the suggested model fit in well with the data in terms of the one-factor model, CMB was unlikely to be a serious issue.

4.3 Hypothesis testing

AMOS was subsequently selected for the estimation of a structural model through which to assess the standardized values of item loadings and the path coefficients between the variables (Bagozzi and Yi, 1988; Rialti *et al.*, 2017; Zollo *et al.*, 2017). With regards to the absolute fitting indexes of the model, the relative test of $\chi2$ ($\chi2/df$) was 1.404, meaning that both indexes showed acceptable levels. The RMSEA of 0.040 was considered suitable as a value below 0.075 is expected for an acceptable fit. Finally, the relative fit indexes were all in excess of 0.90 (GFI = 0.998; CFI = 0.999; NFI = 0.999; IFI = 0.999; TLI = 0.996), suggesting an adequate fitting of the model (Bentler, 1990). Figure 2 shows the scores of the estimated coefficients.

Figure 2. Structural Model



Notes:
**p-value<0.01
R^2= explained variance

Source: Authors' elaboration using AMOS v.21

The Baron and Kenny (1986) approach was followed to evaluate the eventual mediating role of knowledge management capabilities. The authors initially tested the same model without any kind of mediation. The results of this preliminary test showed the existence of direct relationships between BDA capabilities, explorative innovation (β=+0.66, $p<0.01$), and exploitative innovation (β=+0.73, $p<0.01$). Yet, when knowledge management capabilities were considered, they were shown to be partial mediators of the aforementioned relationships. Indeed, when a mediating factor was considered, the following relationships emerged: (1) BDA capabilities→knowledge management capabilities (β=+0.74, $p<0.01$); (2) BDA capabilities→explorative innovation (β=+0.57, $p<0.01$); (3) BDA capabilities→exploitative innovation (β=+0.53, $p<0.01$); (4) knowledge management capabilities→explorative innovation (β=+0.13, $p<0.01$); (5) knowledge management capabilities→exploitative innovation (β=+0.26, $p<0.01$). Thus, hypotheses H1 to H5 were statistically supported.

In addition to this, analysis of the other path coefficients showed that explorative innovation significantly influences the achievement of strategic flexibility (β=+0.42, $p<0.01$), providing statistical support for H6. Therefore, the organisation's inner ability to scan the market for new and emerging opportunities was positively related to the organisation's readiness to adjust to changes. For H7, however, exploitative innovation was a relevant antecedent strategic flexibility (β=0.50, $p<0.01$). These phenomena are in line with existing research on dynamic capability theories and BDA. Information from big data could allow organisations to better identify or exploit emerging opportunities and be more reactive to changes (Rialti *et al.*, 2019a; b).

5. Discussion and managerial implications

The results of our analysis show that BDA capabilities could be a significant antecedent to large organisations' strategic flexibility. Knowledge management capabilities and ambidexterity also play an important role. These factors are intrinsically intertwined with the relevant informative potential of big data datasets. Big data consists of large datasets, heterogeneous and complex enough to potentially contain an almost limitless amount of information concerning customers and competitors (Erevelles *et al.*, 2016). In the absence of the right capabilities, no organisation could reap the full benefits of big data. BDA capabilities are thus fundamental in turning unorganised pieces of information into metrics, forecasts, and insights about individual customers or competitors' actions (Chen *et al.*, 2012; Xu *et al.*, 2016). In a similar fashion, knowledge management capabilities matter in the big data era. Information emerging from the analysis of big data should be assimilated, distributed, and managed within the organisation, and knowledge acquisition, application, and sharing capabilities are fundamental in ensuring that the right insights reach those that can make the most of them (O'Connor and Kelly, 2017; Ferraris *et al.*, 2019; Santoro *et al*., 2019). Knowledge fluxes spanning the organisation are useless if not properly distributed. As such, the ambidextrous traits of the organisation could be fundamental in an era of big data, as they allow the organisation to react to change, as shown in research concerning organisational flexibility (Caputo *et al.*, 2016). The interplay between BDA capabilities and knowledge management capabilities can, therefore, be considered the main factor impacting the transformation of pieces of information into something of value. Hence, an organisation's capable of developing BDA without resistance from employees, managers, or stakeholders, but also characterized by existing knowledge management practices, could potentially be capable of better scanning their environment and better identifying which opportunities to exploit.

Moving on from these considerations, this research contributes to the stream of literature exploring the effects of organisational BDA capabilities. In particular, this research contributes towards the literature on BDA capabilities, knowledge management, and ambidexterity (i.e. Dubey *et al.*, 2018; Rialti *et al.*, 2018; 2019a) by empirically exploring their relationship with strategic flexibility. This contribution represents a novelty in the current stream of scholarly literature. Previous researchers have focused either on the theoretical exploration of the phenomenon (Rialti *et al.*, 2018) or on different facets of flexibility, i.e. supply chain flexibility (Dubey *et al*., 2018). In this study, the authors have built upon the well-known relationship between ambidexterity and flexibility in order to test the importance of knowledge management capabilities in diffusing information extracted from big data through BDA capabilities. The ability to diffuse information throughout the organisation properly is indeed fundamental in transforming information from big data into management decisions and, ultimately, performance. Henceforth, this research also expands upon existing literature on the importance of the knowledge management capabilities and procedures used to manage big data (Ferraris *et al*., 2019). The findings may then pave the way for future research on BDA and ambidexterity by providing valuable insights pertaining to the fact that knowledge management processes are necessary for the era of big data.

With regards to practical implications, managers should pay particular attention to their company's channels of knowledge by investing and developing infrastructures that foster the knowledge management and BDA capabilities of the company (Gupta and George, 2016). As shown in this study, BDA capabilities, together with knowledge management capabilities, are clear antecedents of an ambidextrous approach to innovation, which ultimately results in superior performance. Managers should, therefore, invest in developing these two capabilities, ultimately creating strategic flexibility. In particular, the study shows that strategic flexibility can be indirectly achieved by investing in effective BDA and knowledge management practices and systems across all levels of the company.

Managers are advised to invest in flexible architectures that can make knowledge available both throughout the company and outside of its boundaries. An example of a structure built for this purpose would be the data lakes, which permit the collection, storage, and sharing of several types of data, making it available to the entire organisation as well as its partners. In doing so, the company could foster the interoperability and the diffusion of knowledge through its structure, gain insights from partners, and foster its ability to explore and exploit new forms of innovation (Gupta and Giri, 2018). In summary, when investing in effective BDA and knowledge management capabilities and tools, ambidexterity and strategic flexibility can emerge autonomously as outcomes.

Furthermore, moving on from our results on knowledge management in the era of big data, it is important to suggest that managers be mindful of the human element of BDA. The use of good architectures in an organisation are insufficient if the people behind them are not capable of managing a system's complexity or are unable to relate to each other and share their knowledge.

6. Conclusions, limitations, and suggestions for future research

This research highlighted the role of BDA capabilities and knowledge management capabilities in fostering a company's ambidexterity and strategic flexibility. On the one hand, BDA capabilities permit the company to identify, store, and make available information crucial to the whole organisation. On the other hand, knowledge management capabilities permit the identification of the correct information needed to capture and store relevant knowledge, such as customer preferences and knowledge about the market (Lu and Ramamurthy, 2011). The interplay between these two capabilities allows the company to be ambidextrous and strategically flexible, ultimately resulting in superior performance (O'Reilly and Tushman, 2013; Rojo *et al.*, 2016). As a result, this study highlights the importance of having effective and efficient information systems that encompass both BDA and knowledge management capabilities.

Aside from these noteworthy findings, this research still has some limitations. First of all, in this research, BDA and knowledge management capabilities have been considered as single aggregate constructs. There is, therefore, a need to unpack these two constructs and test whether or not, and to what extent, they influence ambidexterity and strategic flexibility. Next, this study has been deployed using a sample of managers working for large companies in continental Europe. As a result, it would be useful to extend the research into different countries in order to test whether or not the findings proposed are valid and reliable in other contexts as well. In countries characterized by lower technological capabilities, results may vary. Finally, it would be useful to explore whether or not BDA capabilities matter in a sample comprised of managers working for SMEs.

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