Big data analytics capabilities and performance: Evidence from a moderated multi-mediation model

DOI:10.1016/j.techfore.2019.119781

Big Data Analytics Capabilities and Performance: Evidence from a Moderated Multi-Mediation Model

Abstract

Big data analytics (BDA) have the power to revolutionize traditional ways of doing business. Nevertheless, the impact of BDA capabilities on a firm's performance is still not fully understood. These capabilities relate to the flexibility of the BDA infrastructure and the skills of the management and the firm's personnel. Most scholars explored the phenomenon from either a theoretical standpoint or neglected intermediate factors, such as organizational traits. This article builds on the dynamic capabilities view to propose and empirically test a model exploring whether organizational ambidexterity and agility mediate the relationship between BDA capabilities and organizational performance. Using data from surveys of 259 managers of large European organizations, we tested a proposed model using bootstrapped moderated mediation analysis. We found that organizational BDA capabilities affect a firm's ambidexterity and agility, which, in turn, affect its performance. These results establish ambidexterity and agility as positive mediators in the relationship between organizational BDA capabilities and a firm's performance. Furthermore, the organizational resistance to the implementation of information management systems and the fit between the organization and these systems also moderated this relationship. Practical implications for managers are also discussed.

Keywords: *Agility, Ambidexterity, Big Data, Big Data Analytics (BDA), Management Information Systems, Organizational Performance.*

1. Introduction

The emergence of big data has revolutionized old business models (McAfee & Brynjolfsson, 2012) as well as the management of organizational knowledge (Pauleen & Wang, 2017; Khan & Vorley, 2017). Big data are large, heterogeneous datasets containing different types and quantities of information (Manyika, Chui, Brown, Bughin, Dobbs, Roxburgh & Byers, 2011). Thanks to big data, managers today may know their organizations, their competitors and their customers better than ever (Dubey, Gunasekaran, Childe, Papadopoulos, Luo, Wamba, & Roubaud, 2017; Wang, Kung, & Byrd, 2018). Specifically, big data allows managers to monitor the status of each internal process, the performance of business units, processes and assets, as well as bottlenecks in the supply chain in real time (Akter, Wamba, Gunasekaran, Dubey & Childe, 2016; Roßmann, Canzaniello, von der Gracht, & Hartmann, 2018; Cappellesso & Thomé, 2019). Big data can also access new and updated data from the Internet to identify potential maneuvers by competitors (Erevelles, Fukawa & Swayne, 2016; Scuotto, Ferraris & Bresciani, 2016). In addition, big data can provide producers with information about their customers' behavioral patterns, requests and complaints (Hofacker, Malthouse & Sultan, 2016), both on the aggregate level, in the form of information about their customer base, and on the individual level, in the form of details about the individual customer's behavior over time.

Given the diffusion of big data, companies need to develop organizational big data analytics capabilities (or BDA) to extract relevant information and make sense of it to make decisions. Organizational BDA capabilities are an ensemble of capabilities that include infrastructure flexibility, management capabilities and personnel capabilities (Wamba, Gunasekaran, Akter, Ren, Dubey & Childe, 2017). Organizations that promote their BDA capabilities may have several different outcomes. Nevertheless, most of the existing literature agrees that BDA capabilities could influence organizations' economic performance. For example, Erevelles *et al.* (2016) pointed out how BDA capabilities may impact an organization's marketing capabilities and ability to react in a timely fashion to develop new marketing strategies. Their study showed how an organization's performance could improve as a result of new information about customers. In contrast, Tan, Zhan, Ji, Ye & Chang

(2015) and Wang *et al.* (2018) demonstrated how BDA capabilities have the power to revolutionize the management of the supply chain. Similarly, Kwon, Lee & Shin (2014) stressed how BDA could improve internal operations and processes, including organizational efficiency (Rialti, Marzi, Ciappei & Busso, 2019). Wamba *et al.* (2017) also observed how BDA capabilities could affect dynamic capabilities. Therefore, information from big data can impact an organization's performance by influencing its capability and adaptability. Large organizations benefit the most from data and BDA because they are well-positioned to put it to use (Prescott, 2014; Wamba & Mishra, 2017; Wamba *et al.*, 2017).

Notwithstanding the evidence about the impact of BDA, some gaps still exist in this stream of literature. Indeed, scholars have just begun to understand the complex relationships between the development of BDA and organizational performance. On one hand, part of the research is still theoretical (i.e., Rialti, Marzi, Silic & Ciappei, 2018) or at most qualitative (i.e., Cillo, Rialti, Del Giudice & Usai, 2019; Santoro, Fiano, Bertoldi & Ciampi, 2018). On the other hand, quantitative research on BDA capabilities and performance is still in its infancy (Dubey *et al.*, 2017; Wamba *et al.*, 2017). There is a clear need to explore which organizational traits could be influenced by BDA capabilities and their effect on performance. In addition, we also must identify the factors that prevent the successful implementation of BDA within organizations. This is the research gap we aim to fill with this paper.

Our goal is to propose and empirically test several hypotheses about the factors that affect the relationship between big data and organizational performance. We use a dataset derived from a survey conducted among 259 managers of large organizations involved in big-data projects to assess the effect of two mediators (ambidexterity and agility) and two moderators (organizational resistance to the implementation of information management systems and the fit between such systems and the organization) to conduct the test. We decided to focus only on large organizations because they are the major consumers and beneficiaries of big data (De Mauro, Greco, Grimaldi & Ritala, 2018).

Additionally, BDA capabilities require major investments that can be made only by large organizations (Cillo *et al.*, 2019; Gölgeci, Ferraris, Arslan & Tarba, 2019).

The research contributes to the existing literature in multiple ways. First, it reveals how information coming from big data could influence a firm's economic results, highlighting the role of organizational ambidexterity and agility in this relationship. Demonstrating this impact also underscores the importance of BDA in the achievement of ambidexterity—the ability to adapt to changes by using existing resources—as well as the importance of agility. Second, the study proposes and empirically tests an original moderated multi-mediation model that provides a better understanding of the complex interrelationships among the factors that allow companies to gain a competitive advantage from big data. Third, we highlight how organizational characteristics may prevent the successful application of big data by investigating the relevance of the fit between the organization and its information management system and the resistance to the implementation of such systems with regard to BDA-related projects. The findings demonstrate the expected results of investing in BDA and provide practical guidelines that companies can use to develop their BDA capabilities.

The paper is organized as follows. The following section includes a review of the existing literature on BDA, organizational BDA capabilities, and the potential effects of big data and BDA on a firm's performance. In addition, it also explains the interconnections among BDA, ambidexterity, agility, and performance. Building on this literature, we developed a model with nine hypotheses. The third section deals with the sampling procedure and the explanation of the methodological process. We used Hayes' multi-level mediation SPSS macro (2013) as the main method to analyze the collected data. We chose this method because, as a nonparametric resampling strategy, it requires no assumption of normality, it estimates indirect and interactive effects, its confidence intervals are very accurate, and it provides an effective test of the model's predictive validity. The fourth section reports the main results related to the mediators and moderators. Section five discusses these results, along with their implications. The last section describes the limitations of the study and provides suggestions for future research.

2.Theoretical Background and Development of Hypotheses

2.1. BDA Capabilities in Large Organizations

Big data differ from traditional datasets such as those in Excel files in at least seven ways: volume, velocity, variety, veracity, value, variability and visualization. Therefore, the term "big data" has frequently been used to describe datasets that are both large and complex, and cannot be analyzed with traditional statistical models (Manyika *et al.*, 2011).

Given these differences, big data management poses several significant challenges to organizations. To utilize this information, they must develop "big data architectures," which are networks composed of several processors, machines and databases that can collect, process, store and analyze big data (Yi, Liu, Liu & Jin, 2014). Such architectures need to be based on data lakes, which are systems or repository of data stored in their original format. A data lake is usually a single store of all enterprise data including raw copies of source system data and transformed data, derived from sensors monitoring machines or internal process (Gupta & Giri, 2018). Next, organizations may need to rely on nested computer networks capable of processing different kinds of data simultaneously. Such networks need to be based on open-source software capable of parallel computing and able to ensure inter-organizational operability. These characteristics allow organizations to collect, categorize, store and analyze data stored in repositories (Labrinidis & Jagadish, 2012). These architectures must be agile enough to adapt to changing organizational structures (Rialti *et al.*, 2018).

However, the machinery alone is insufficient for dealing with the complexity of big data management. Organizations must invest in hiring and training professionals for this task (Wamba *et al.*, 2017). For instance, big data analysts, scientists and engineers need to be skilled in R, Python, Hadoop, Not Only SQL (NoSQL) data models, schema-less data retrieval, and other tools that use artificial intelligence paradigms (LaValle, Lesser, Shockley, Hopkins & Kruschwitz, 2011). Hence, simple personnel re-training may not be sufficient to meet the challenges of big data. Indeed, the entire culture of the organization should be transformed according to the paradigms of the so-called "big data culture" (Tallon & Pinsonneault, 2011). In this culture, decisions are data driven, and employees should not be afraid to rely exclusively, or almost exclusively, on machines and data when making business-related decisions (Rialti *et al.*, 2019). Consequently, managers' resistance to computer-aided decision-making should be reduced to reap the advantages of big data (Akter *et al.*, 2016).

In addition to these main requirements, Wamba *et al.* (2017) outlined the notion of organizational BDA capabilities, which are an ensemble of capabilities related to the "ability to mobilize and deploy BDA-based resources in combination with other resources and capabilities" (p. 357). The authors highlighted three capabilities that are fundamental for any organization: the flexibility of the BDA infrastructure, BDA management capabilities and BDA personnel capabilities. BDA infrastructures, which are the ensemble of information systems capable of collecting, storing, processing and analyzing big data, should be able to adapt themselves to different types of data. This capability is fundamental to ensuring that technologies will be able to process different data flows and formats in any situation (Rialti *et al.*, 2018). BDA managerial capabilities are critical with regard to selecting and implementing the right BDA infrastructure and identifying the right information to extract from the datasets (Ferraris, Mazzoleni, Devalle & Couturier, 2018). Managers should be able to decide which technical solution is the best for their organization. Similarly, they need to have enough data analytics skills to make the right decisions when new data become available (Provost & Fawcett, 2013).

Finally, the personnel should also be skilled in BDA for several reasons. First, the presence of people with such skills reduces the likelihood of the organization's rejecting BDA or resisting the implementation of new information management systems and improves the functioning of the BDA infrastructure. Additionally, since employees are often those analyzing the data, they need the skills to identify the right data to be analyzed (Wamba *et al.*, 2017) and draw appropriate conclusions from their assessments. The literature indicates that these capabilities may create a competitive advantage for any organization (McAfee & Brynjolfsson, 2012).

As previously noted, in order for organizations to leverage the benefits of BDA, they must make significant investments. Therefore, small and medium-size businesses usually lack the capability to invest in systems such as parallel computing and data lakes (Raguseo & Vitari, 2018) or hire or re-train the necessary personnel. Thus, it is generally only large companies that can reap the benefits of BDA. Examples include the report of Davenport, Barth & Bean (2012) about how large organizations utilizing the Internet of Things and BDA can make their productive processes more efficient. Similarly, Hofacker *et al.* (2016) pointed out how big data could help retailers improve the customers' overall experience. Johnson, Friend & Lee (2017) and Rialti *et al.* (2018) assessed how BDA helps large organizations identify opportunities. Finally, Braganza, Brooks, Nepelski, Ali & Moro (2017) noted how BDA helps large organizations utilize their existing resources to exploit new opportunities.

2.2. Organizational BDA Capabilities, Ambidexterity and Performance

As highlighted in the previous section, organizational BDA capabilities are related to a structural aspect, the BDA infrastructure, as well as to HR management and organizational dynamics. Personnel and managerial BDA capabilities relate to organizational routines. Therefore, it is understandable that existing studies on BDA have used dynamic capabilities as their main theoretical approach (Akter *et al.*, 2016; Wamba *et al.*, 2017). Teece, Pisano, & Shuen (1997) coined the term "dynamic capabilities" to refer to an organization's ability to adapt to the changing environment in an adequate and timely fashion by reconfiguring internal or external processes and resources based on existing competencies. While some definitions link dynamic capabilities to organizational improvisation, they actually consist of "identifiable and specific routines" (Eisenhardt & Martin, 2000, p. 1107). Indeed, some organizational routines and processes are capable of diffusing into the best practices within an organization.

According to Eisenhardt and Martin (2000), organizational routines may be broken down into smaller routines or processes that are the “bricks” forming a complete routine or process. In particular, the standalone routines that derive from BDA managerial and personnel practices may represent bricks that can be utilized in different situations, thus creating a competitive advantage for an organization (Braganza *et al.*, 2017). Given that BDA infrastructures are usually extremely flexible, inter-operable, scalable, and capable of adapting to different kinds of data from different contexts, they are also capable of ensuring the flow of information over time and in any situation (Rialti *et al.*, 2018). It is then clear how BDA and BDA capabilities may influence a firm's performance (Wamba *et al.*, 2017). Such outcomes also accord with studies assessing how information management systems such as BDA (Bloch, Blumberg & Laartz, 2012) create value (Melville, Kraemer & Gurbaxani, 2004).

Research has also established that dynamic capabilities can have a positive effect on a firm's performance because they are indicative of a greater degree of organizational ambidexterity (O'Reilly & Tushman, 2008). Organizations that can re-arrange existing resources and routines to address new problems are also better able to identify changes in the environment and exploit opportunities. Dynamic capabilities related to BDA capabilities could improve their ability to identify new opportunities and threats. Information extracted thanks to BDA allows businesses to identify new opportunities and benefit from them (Rialti *et al.*, 2018). According to the same reasoning, information management systems that can adapt to different situations and data may also help firms identify and exploit new opportunities (Lu & Ramamurthy, 2011). Consequently, given that ambidexterity may influence performance, it may represent an intermediate variable between organizational BDA capabilities and a firm's performance. Thus, we propose the following hypotheses:

H1: *Organizational BDA capabilities are positively related to superior performance*.

H2: *Organizational BDA capabilities are positively related to a firm's ambidexterity.*

H3: *Ambidexterity is positively related to superior performance. Hence, ambidexterity mediates the relationship between organizational BDA capabilities and a firm's performance.*

2.3. Organizational BDA Capabilities, Agility and Performance

Organizational agility, meaning the ability of a business to renew itself and react quickly when necessary (Teece, Peteraf & Leih, 2016), derives directly from a firm's ability to adapt existing assets to new situations. Indeed, agility is often connected to an organization's dynamic capabilities. In cases in which the architectures and procedures required to process information do not represent a burden to an organization's dynamism, its agility may increase significantly (Tarafdar & Qrunfleh, 2017). Such a phenomenon is linked to the fact that abundant information flowing freely within an organization could make people aware of what needs to be done. These findings also emerged in the literature exploring the importance of BDA capabilities (Rialti *et al.*, 2019). Specifically, researchers have noted that, thanks to information extracted by BDA infrastructures, managers and personnel with strong BDA skills can make quicker decisions, which may affect an organization's ability to react (McAfee & Brynjolfsson, 2012; Wamba & Mishra, 2017). These results demonstrate how organizational BDA capabilities influence a firm's agility (Lu & Ramamurthy, 2011). In addition, agility is frequently associated with better organizational performance, showing how an adaptable and agile organization can thrive even in difficult times. Thus, we posit that:

H4: *Organizational BDA capabilities are positively related to agility.*

H5: *Agility is positively related to superior performance. Hence, agility mediates the relationship between organizational BDA capabilities and a firm's performance.*

2.4. Ambidexterity and Agility

As noted earlier, ambidexterity "is vital to pursue both […] exploration and exploitation for its innovative redesign of operational processes and continuous productivity improvement simultaneously” (Lee, Sambamurthy, Lim & Wei., 2015, p. 402). Studies have established that ambidexterity is related to the improved ability of a firm to respond effectively to market changes and is an antecedent of agility. Improving a firm’s exploitation and exploration capabilities may prompt and promote its reconfiguration and responsiveness, which are two distinguishing characteristics of agile organizations (Lee *et al.*, 2015). In the big data era, researchers have established that companies that utilize advanced IT systems that foster ambidexterity can become agile because information may make internal operations more efficient and streamlined. Thus, we hypothesize that:

H6: *Organizational ambidexterity is a critical antecedent of agility.*

2.5. Moderators from the information management system literature

The components of BDA infrastructures share the same theoretical foundation as any other management information system. BDA infrastructures are fundamental for decision-making, for the coordination, control and analysis of processes, and for the visualization of information. These elements accord with the definition of information management systems (Chen, Chiang & Storey, 2012). The implementation of BDA infrastructures and that of information management systems may have similar dynamics, making it possible to identify the same antecedents. Researchers have established that the better the alignment between an information management system and an organization’s characteristics is, the stronger the effect of the information management system (Iivari, 1992; Kanellis, Lycett & Paul, 1999). Specifically, the information management system’s functionalities must be aligned with the scope of the organization (Henderson & Venkatraman, 1993; Pandey & Dutta, 2013). Similarly, there must also be an alignment between the users’ capacities and the system’s characteristics, between the data that the system should process and the data existing within the organization’s datasets, and between the existing procedures and the new ones that will exist after the implementation of the information management system (Hong & Kim, 2002). Thus, the development of BDA capabilities is related to the fit between such new capabilities and those already existing within an organization.

Another factor of importance in the development of BDA capabilities is how resistant an organization is to change. If existing IT infrastructures are totally incompatible with BDA, managers do not want to make computer-aided decisions, and employees are incapable of running the systems, it may be impossible to develop BDA. These issues are consistent with the research on organizational resistance to change (Rafferty & Jimmieson, 2017). Thus, we propose that:

H7 a, b, c: *The fit between the organization and the information management system may positively moderate the relationships between organizational BDA capabilities and (a) ambidexterity, (b) agility or (c) performance.*

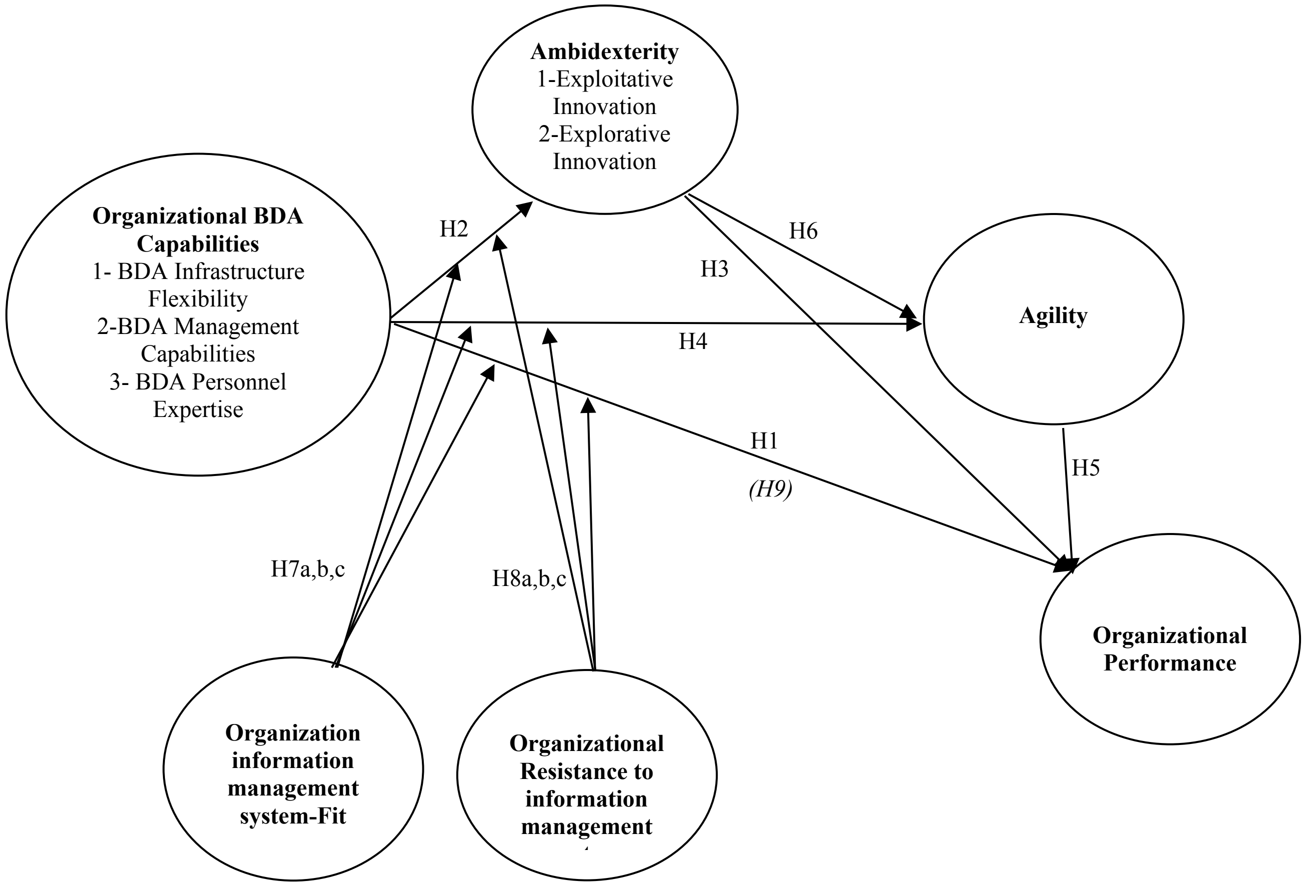
H8 a, b, c: *Organizational resistance to the implementation of an information management system may negatively moderate the relationship between BDA capabilities and (a) ambidexterity, (b) agility or (c) performance.*

2.6. Conceptual Model

Building on the previous hypotheses, the authors developed the conceptual model proposed in Figure 1 with several mediators and moderators. The final model consists of 9 hypotheses. Indeed, the main objective of this research is to investigate how organizational ambidexterity and agility may mediate the relationship between organizational BDA capabilities and performance. Such a complex model is justified by the necessity to develop a model including all the direct effect and the mediated effects between all the variables. The authors also included in the analysis the final hypothesis concerning the direct relationship between organizational BDA capabilities and performance.

H9*: The relationship between organizational BDA capabilities and performance is mediated by ambidexterity and agility.*

Figure 1 - Hypothesized Model



Notes:
H7 indicates the moderating effect of the fit between an organization and the information management system
H8 indicates the moderating effect of the organization's resistance
H9 indicates the multi-mediation hypothesis (the mediating effect of ambidexterity and agility on BDA → the relationship with the firm's performance)

Source. Authors' Elaboration

3. Method

3.1 Sampling

To test our hypotheses, we used data from a sample of European managers collected with the help of a UK-based marketing research company. The company that was contacted to collect the data owns a database containing information from about 10,000 UK, EU and US managers. Among these, about 8,500 of them are either from the UK or the EU and have managerial roles in what the EU defines as large organizations. Additional screening criteria were used to create the final pool of potential respondents, including 1) employment status (full time, part-time); 2) role within the organization (partner, managing director, senior manager, middle manager, junior manager); 3) expertise in big data (expert level); 4) leadership position (having more than two direct subordinates); 5) industry (agriculture, adult/college education, broadcasting, computer/electronic, construction, design/industrial design, electricity/oil and gas, finance/insurance, hotel and tourism, information/data processing/communication, marketing, marketing research, military, mining, product development, publishing, retail and wholesale, scientific/technical services, software/software development, pharmacy/healthcare in general, telecommunication) and organization's typology (large private, publicly listed).

In the end, the survey was administered to a sample composed of 862 managers. We received 259 completed questionnaires in the period between September and December 2018. This response rate of 30.04% accords with the usual response rate for surveys from managers (Baruch, 1999). Among the respondents, 125 were men (48.3%), and 134 (51.7%) were women. As reported in Table 1, most of them (49%) had more than 10 years of experience with information management systems.

To avoid non-response bias (Rogelberg & Stanton, 2007), in May 2018 we pretested the questionnaire by emailing a link to an electronic survey to seven scholars with a strong background in either information management systems or big data. We took this step to ensure that the survey was carefully structured, easy to complete, of an adequate length, and had clear and unambiguous questions (Laudano, Zollo, Ciappei & Zampi, 2018). After this pre-test, no modifications or corrections were made to the final questionnaire. We also evaluated the sample for potential non-response bias by conducting a wave analysis (Armstrong & Overton, 1977), which compared early (September-October 2018) and late (November-December 2018) respondents according to key variables such as age, gender, employment, and the dependent variables of our hypothesized model. The results of *t*-tests across such variables showed no significant differences between the early and late groups, thus indicating that non-response bias was not a concern.

Table 1 – Summary of the Sample's Characteristics

Control Variable	n	%
Gender		
Male	125	*48.3*
Female	134	*51.7*
Age		
18-24	30	*11.5*
25-29	45	*17.3*
30-39	105	*41*
40-49	55	*21.1*
More than 50	24	*9.2*
Education		
Primary school	1	*0.4*
Secondary school	19	*7.3*
High school	55	*21.2*
Bachelors' degree	122	*47.1*
Masters' degree	44	*17.0*
PhD	12	*4.6*
Other	6	*2.4*
Years of experience		
Less than 1 year	5	*1.9*
1-5 years	60	*23.2*
5-10 years	67	*25.9*
More than 10 years	127	*49.0*
Industry		
Adult/college education	2	*0.8*
Broadcasting	1	*0.4*
Computer/electronic	28	*11.2*
Electricity/oil and gas	8	*3.1*
Finance/insurance	20	*7.7*
Hotel and tourism	6	*2.3*
Information/data processing/communication	27	*10.4*
Manufacturing	16	*6.2*
Marketing	8	*3.1*
Marketing research	4	*1.5*
Retail and wholesale	31	*12*
Scientific/technical services	43	*16.6*
Pharmacy/healthcare in general	29	*12.2*
Telecommunication	14	*5.6*
Other	22	*6.9*
Organization's turnaround		
50-99 Million (€)	202	*78*
100 Million - 1 Billion (€)	33	*12.7*
More than 1 Billion (€)	24	*9.3*

Source: Authors' elaboration

3.2 Measures

The entire survey contained 83 items. We measured organizational BDA capabilities through the 49-item scale used by Wamba *et al.* (2017). In accordance with previous research, we considered organizational BDA capabilities a second-order variable (Gunasekeran, Yusuf, Adeleye &

Papadopoulos 2018; Mikalef & Pateli, 2017). The selected variables derived from three first-order variables, namely the flexibility of the BDA infrastructure (11 items), BDA management capabilities (21 items), and BDA personnel expertise (17 items).

Statements related to the flexibility of the BDA infrastructure included those related to connectivity (four items, such as "Compared to rivals within our industry, our organization has the foremost available analytics systems"), compatibility (three items, such as "Software applications can be easily used across multiple analytics platforms") and modularity (four items, such as "Reusable software modules are widely used in new system development") as latent variables.

Statements related to BDA management capabilities included those related to planning (four items, such as "We continuously examine innovative opportunities for the strategic use of business analytics"), decision-making (five items, such as "When we make business analytics investment decisions, we estimate the effect they will have on the productivity of the employees' work"), coordination (four items, such as "In our organization, business analysts and line people meet regularly to discuss important issues") and control (eight items, such as "In our organization, the responsibility for analytics development is clear") as latent variables.

Finally, statements related to BDA personnel expertise included those related to technical knowledge (five items, such as "Our analytics personnel are very capable in decision support systems (e.g., expert systems, artificial intelligence, data warehousing, mining, etc.)"), , business knowledge (four items, such as "Our analytics personnel are very capable in interpreting business problems and developing appropriate solutions") and relational knowledge (four items, such as "Our analytics personnel work closely with customers and maintain productive user/client relationships") as variables (Wamba *et al.,* 2017).

To measure organizational ambidexterity, we used the 8-item scale of Jansen, Tempelaar, Van den Bosch, & Volberda (2009). We followed the suggestion to consider ambidexterity as a standalone first-order variable. Therefore, we used the two latent variables – explorative innovation (i.e., "Our organization accepts demands that go beyond existing products and services") and exploitative innovation (i.e., “We increase economies of scale in existing markets”) – to create the first-order organizational ambidexterity variable.

To measure organizational agility, we used Cegarra-Navarro, Soto-Acosta, & Wensley (2016) 6-item scale (i.e., “We have the ability to rapidly respond to customers' needs”). Previous researchers have used this scale successfully to explore the impact of information systems and technologies on organizational agility (Soto-Acosta & Cegarra-Navarro, 2016).

To measure organizational performance, we used Gibson & Birkinshaw’s (2004) 4-item scale (i.e., “The organization does a good job in satisfying our customers”).

Finally, we measured organizational resistance to the implementation of information management systems using Hong & Kim’s (2002) 5-item scale (i.e., “There have been many users resisting the BDA implementation”). We also used their 11-item scale to assess the fit between the organization and the information management system (i.e., “The processes built in BDA information systems meet all needs required from organizational processes”).

Respondents rated the items on a 7-point Likert scale ranging from 1=strongly disagree to 7=strongly agree.

4. Analysis and Results

4.1. Descriptive statistics and correlation analysis

The mean and standard deviation of all constructs along with the Pearson’s r values are reported in Table 2. The strongest correlation was between business knowledge and technical knowledge (r=0.807; p<0.01). The second strongest was between coordination and planning (r=0.805; p<0.01).

Table 2 - Correlation matrix

	Mean	*SD*	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*	*15*
1) Connectivity	4.37	1.62	*(0.768)*														
2) Compatibility	4.67	1.62	0.674*	*(0.842)*													
3) Modularity	4.14	1.53	0.655*	0.517*	*(0.752)*												
4) Planning	4.63	1.56	0.708*	0.656*	0.595*	*(0.887)*											
5) Decision making	4.84	1.53	0.594*	0.503*	0.624*	0.725*	*(0.844)*										
6) Coordination	4.56	1.61	0.544*	0.543*	0.520*	0.656*	0.600*	*(0.861)*									
7) Control	4.55	1.53	0.718*	0.705*	0.665*	0.805*	0.706*	0.764*	*(0.919)*								
8) Technical knowledge	4.78	1.48	0.632*	0.528*	0.616*	0.686*	0.676*	0.645*	0.777*	*(0.909)*							
9) Business knowledge	4.99	1.52	0.532*	0.581*	0.526*	0.693*	0.650*	0.655*	0.749*	0.757*	*(0.918)*						
10) Relational knowledge	4.89	1.52	0.577*	0.594*	0.556*	0.701*	0.654*	0.661*	0.745*	0.717*	0.807*	*(0.869)*					
11) Ambidexterity	4.63	1.65	0.575*	0.470*	0.551*	0.647*	0.609*	0.488*	0.623*	0.538*	0.496*	0.535*	*(0.842)*				
12) Agility	4.91	1.51	0.565*	0.586*	0.568*	0.622*	0.650*	0.625*	0.635*	0.560*	0.558*	0.545*	0.685	*(0.881)*			
13) Performance	4.74	1.37	0.642*	0.650*	0.625*	0.573*	0.550*	0.582*	0.538*	0.602*	0.633*	0.615*	0.519	0.599	*(0.852)*		
14) Resistance	4.05	1.55	0.280*	0.255*	0.185*	0.082	0.125*	0.082	0.189*	0.265*	0.250*	0.291*	0.301	0.222	0.093	*(0.940)*	
15) Fit	4.37	1.44	0.322*	0.350*	0.348*	0.403*	0.388*	0.425*	0.390*	0.428*	0.375*	0.440*	0.609	0.623	0.536	0.379	*(0.904)*

Notes:
** *p*-value < 0.01
Cronbach's Alpha reported on diagonal

Source: Authors' elaboration

To check for potential multicollinearity, we estimated the variance inflation factors (VIFs) (Lee *et al.,* 2016) using the SPSS collinearity test (Field, 2013). Each of the independent variables exhibited a VIF value below the threshold of 3.0 (Picón, Castro & Roldán*,* 2014), ranging from 1.50 to 2.80, with a mean of 2.35, thus indicating no problem with multicollinearity. Using the 0.80 benchmark for the strength of the correlations (Franke, 2010), as Table 4 shows, none of the variables were highly correlated. As a result, there were no multicollinearity concerns. Hence, all of the independent variables were included in the moderated mediation analysis.

4.2 Confirmatory factor analysis

A confirmatory factor analysis (CFA) was conducted using AMOS v. 22 (Arbuckle, 2013). The maximum likelihood function of AMOS was used to estimate parameters and test the hypothesized relationships among the variables (Bagozzi & Yi, 1988). We first estimated a measurement model to evaluate the goodness-of-fit indexes and confirm the parsimony of the hypothesized model (Bagozzi & Yi, 1988).

Concerning the absolute fit indexes, the $\chi 2$ was significant ($\chi 2 = 143.192$, $p<0.01$) and the relative $\chi 2$ provided an acceptable fit with a *t*-test of $\chi 2/df = 2.11$ (less than 3, as required) (Bagozzi & Yi, 1988; Bentler, 1990). Next, the global fit index (GFI) (0.995) suggested a satisfactory fit (higher than 0.9, as required). Finally, the root means square error of approximation (RMSEA) of 0.062 suggested an acceptable model fit, being less than 0.07, as required (Bentler, 1990).

Concerning the relative fit indexes, the most commonly used are the comparative fit index (CFI), the incremental fit index (IFI), the normed fit index (NFI), and the Tucker-Lewis index (TLI), also known as the non-normed fit index (Bagozzi & Yi, 1988). All of the relative fit indexes showed acceptable values, being higher than 0.9, as required. Specifically, CFI = 0.945; IFI = 0.930; NFI = 0.922; TLI = 0.938 (Bentler, 1990).

The CFA showed that all of the factor loadings – the path coefficients between the observed variables (indicators) and the latent variables – were significant ($p < 0.01$). To evaluate the internal consistency of the indicators, we estimated the composite reliability (CR) for each latent variable. CR values were all higher than 0.6, as required (Bagozzi & Yi, 1988). Moreover, the convergent validity was also assessed through the average variance extracted (AVE) of each latent variable (Zollo, Faldetta, Pellegrini & Ciappei, 2017; Zollo, Yoon, Rialti & Ciappei, 2018). All of the variables had an AVE value higher than 0.5, as required (Bentler, 1990).

Finally, we tested for the presence of common method bias by following the procedures suggested by Podsakoff, MacKenzie, Lee & Podsakoff (2003). First, we pretested the scales to eliminate items that were vague from the questionnaire. Second, we conducted Harman's one-factor test to determine if there was a single factor that explained most of the variance. Next, we utilized an AMOS corroborative factor examination to contrast the proposed model and a model that loaded all of the variables onto a single factor (Podsakoff *et al.*, 2003). The examination produced a noteworthy change in $\chi 2$, as required – the $\chi 2$ contrast test with one degree of freedom was 10, much higher than 3.84, which is the basic level related to p1⁄40.05 (Rialti, Zollo, Pellegrini & Ciappei, 2017; Zollo, Laudano, Boccardi & Ciappei, 2019). Our proposed model was a better fit than the one-factor model (Podsakoff *et al.*, 2003).

4.3. Testing the Hypotheses

We tested the moderated mediation hypotheses following the procedure proposed by Hayes and colleagues (Hayes, 2013; Preacher & Hayes, 2004) and using the SPSS PROCESS macro (v. 2.16). Specifically, to conduct a multiple mediation analysis (model 6 of PROCESS) and a moderation analysis (model 1 of PROCESS), we used the bootstrapping method (based on 5,000 bootstrap samples) and computed 95% bias-corrected lower level confidence intervals (LLCIs) and upper level confidence intervals (ULCIs) around the estimates of the indirect effects (Zollo *et al.,* 2019).

Independent variables such as organizational BDA capabilities should be significantly related to the mediation variables of ambidexterity and agility. After controlling for the effect of the independent variables, the mediation variables should also be significantly related to the dependent variable of performance. According to Hayes (2013), an important indication of mediation is the significance level of the *indirect* effect from organizational BDA capabilities (the "X" variable) to performance (the "Y" variable) through ambidexterity and agility (the "M" variables), as indicated by the *p*-value or the LLCIs and ULCIs. In other words, the *total* effect of organizational BDA capabilities on performance should differ from the *direct* effect of such a relationship, resulting in an *indirect* effect different from zero.

Concerning moderation, the hypothesized moderating variables (the "W" variables, such as the fit between the organization and the information management system and the organizational resistance to the implementation of information management systems) should have a significant effect ($p < 0.05$) on the previously assessed relationships (i.e., organizational BDA capabilities → ambidexterity) and thus modify the original regression weights, either in a positive way (positive moderation such as the fit between the organization and the information management system) or a negative way (negative moderation such as the organizational resistance to the implementation of information management systems). Results are reported in Table 3.

Concerning the mediation analysis, the total effect of organizational BDA capabilities on performance (without considering the mediating variables) was significant and high (β=+0.768; $p <$ 0.01), confirming *H1*. Our empirical evidence also showed that organizational BDA capabilities strongly impacted ambidexterity (β=+0.829; p<0.01), confirming *H2*. Similarly, both organizational BDA capabilities (β=+0.305; p<0.01) and ambidexterity (β=+0.644; p<0.01) had a positive effect on agility, providing statistical support for *H4* and *H6*. While ambidexterity had no significant effect on performance (p>0.10), agility had a positive impact on performance (β=+0.371; p<0.01). Hence, *H3* was not supported but *H5* was confirmed. Finally, the direct effect of organizational BDA capabilities on performance (considering the mediating variables) was significant but reduced (β=+0.586;

p<0.01), showing that ambidexterity and agility had a partial mediation effect. Specifically, the original influence of +0.768 was reduced to +0.586 due to the multi-mediation effect.

Table 3 – Bootstrapped moderated-mediation results

			β	***p***	***Hypothesis***	**(*LLCI; ULCI*)**	***R²***
Mediation:							
H1 - Organizational BDA Capabilities	→	Performance	+0.768	***	Supported	(0.656; 0.879)	45%
H2 - Organizational BDA Capabilities	→	Ambidexterity	+0.829	***	Supported	(0.739; 0.919)	56%
H3 - Ambidexterity	→	Performance	-	0.105	Not Supported	-	45%
H4 - Organizational BDA Capabilities	→	Agility	+0.305	***	Supported	(0.193; 0.745)	72%
H5 - Agility	→	Performance	+0.371	***	Supported	(0.189; 0.554)	45%
H6 - Ambidexterity	→	Agility	+0.644	***	Supported	(0.543; 0.745)	72%
H9 - Ambidexterity + Agility (Direct Effect)	→	BDA → Performance	+0.586	***	Supported	(0.412; 0.759)	42%
Moderation:							
H7a - Organization-Information Management System Fit	→	BDA → Ambidexterity	-	~~.645~~	Not Supported	-	57%
H7b - Organization-Information Management System Fit	→	BDA→Agility	+0.08	*	Supported	(0.036; 0.094)	56%
H7c - Organization-Information Management System Fit	→	BDA → Performance	+0.15	***	Supported	(0.079; 0.208)	46%
H8a - Resistance to Information Management System	→	BDA →Ambidexterity	-0.05	**	Supported	(-0.102; 0.002)	57%
H8b - Resistance to Information Management System	→	BDA → Agility	-	~~0.916~~	Not Supported	-	-
H8c - Resistance to Information Management System	→	BDA -> Performance	+0.14	***	Supported	(0.072; 0.197)	47%

***p-value < 0.01
** p-value < 0.01
* p-value < 0.01

β: regression weight estimate; ***p***: p-value; ***LLCI***: lower level of confidence interval; ***ULCI***: upper level of confidence interval; ***R²***: multiple squared correlation indicating the percentage of variance explained.

Source: Authors' Elaboration

With regard to the moderating variables, the fit between the organization and the information management system had no significant effect on the organizational BDA capabilities → ambidexterity relationship (p > 0.10). Therefore, *H7a* was rejected. Instead, the fit between the organization and the information management system positively moderated the organizational BDA capabilities→agility relationship (β=+0.08; p<0.10) and the organizational BDA capabilities→performance relationship (β=+0.15; p<0.01), providing statistical support for *H7b* and *H7c*, respectively. The organizational resistance to the implementation of information management systems had a negative moderating effect on the organizational BDA capabilities→ambidexterity relationship (β=-0.05; p<0.05), which supported *H8a*. However, it had no significant moderating effect on the organizational BDA capabilities→agility relationship (p>0.10). Therefore, *H8b* was rejected. Finally, the organizational resistance to the implementation of information management systems had a positive moderating effect on the organizational BDA capabilities→performance relationship (β=+0.14; p<0.01), which confirmed *H8c*.

5. Discussion and Managerial Implications

5.1. Theoretical Implications

The results of our analysis highlight how organizational BDA capabilities may re-shape the structure of large organizations. Specifically, we documented that the infrastructures, processes and skills to extract meaningful information from big data may allow large organizations to better identify and exploit opportunities in the markets (Wang, Gunasekaran, Ngai & Papadopoulos, 2016). The research provides various insights into the relationship between big data and a firm's performance.

The most important results from this study show how the organizational ambidexterity and agility derived from BDA capabilities have a positive effect on performance. The causes underlying this phenomenon are understandable, given that an organization capable of responding quickly to changes may outperform its rivals (Chen *et al.*, 2012). Scholars who have documented the value-generating potential of information for organizations and those analyzing the impact of big data using dynamic capabilities as their main theoretical lens have come to similar conclusions (Wamba *et al.*, 2017).

Our results also underscore the fact that a firm's ambidexterity and agility matter. Hence, the development and/or improvement in organizational BDA capabilities can help large organizations in their pursuit of ambidexterity (Raguseo & Vitari, 2018). This finding accords with previous research on organizational ambidexterity. Indeed, the more information an organization can obtain about the state of the market, the more it may be able to identify new opportunities and develop new strategies to exploit them (Raisch & Birkinshaw, 2008). As an organization becomes more capable of accomplishing these goals, it may also become more dynamic and responsive to changes. Ambidextrous organizations can develop new offerings in a shorter period of time and reorganize lean supply chains according to changes in customer demand (Weber & Tarba, 2014). This is particularly true if the ambidexterity derived from ad-hoc information systems allows a company to collect, process and distribute information from outside the organization to its internal members (Lee *et al.*, 2015).

Thus, our study enriches the literature about organizational BDA capabilities and a firm's performance by exploring how ambidexterity and agility can help organizations extract information from big data that they can use to improve their performance (Gupta & George, 2016; Rialti *et al.*, 2019; Wamba *et al.*, 2017). The findings also extend the literature on big data and dynamic capabilities (Akter *et al.*, 2016) by proposing a moderated multi-mediation model useful for understanding the complex dynamics and interrelationships in this context. Hence, organizational big data capabilities are related to broader dynamic capabilities and the ability of the organization to thrive in the competitive arena (Gunasekaran *et al.*, 2018). Our study also contributes to the existing literature about the organizational characteristics that prevent or promote the successful application of big data (Hashem, Yaqoob, Anuar, Mokhtar, Gani & Khan, 2015) by highlighting the different effects of organizational resistance to the implementation of information management systems and the fit between the organization and such systems. Information about these two factors should help researchers and practitioners assess whether an organization will succeed or fail in using big data.

Finally, the research is of value because it focuses on BDA outcomes specifically in large organizations. In such firms, the effects can be substantial, and large companies are those who may benefit the most from big data (McAfee & Brynjolfsson, 2012). Indeed, they are the only kinds of organizations equipped to invest in the infrastructure needed to analyze big data and leverage the results (De Mauro *et al.*, 2018).

Interestingly, BDA infrastructures, which are a constituent factor of BDA capabilities, promote the ambidexterity and agility of large organizations. This finding somewhat contradicts the common beliefs about information management systems (which BDA infrastructures are). In fact, the traditional literature has frequently stressed the fact that information management systems are usually based on rigid infrastructures that might hamper organizational dynamism (Soto-Acosta, Popa & Martinez-Conesa, 2018). One explanation for this discrepancy may be that, due to their technical characteristics, BDA infrastructures demonstrate better operating performance than traditional information management systems. BDA infrastructures - whether based on cloud computing, data lakes or the Internet of Things (Bresciani, Ferraris & Del Giudice, 2018; Caputo, Marzi & Pellegrini, 2016) - are actually based on leaner architectures than traditional information management systems. Another explanation may be that BDA infrastructures provide so much information to large organizations that they improve their ability to identify opportunities, exploit them, and respond dynamically to changes (Grefen, Rinderle-Ma, Dustdar, Fdhila, Mending & Schulte, 2018). Given that large organizations are usually characterized as more rigid and less nimble than small and medium-size businesses (De Mauro *et al.*, 2018), BDA infrastructures may provide a solution to this problem because they are less cumbersome than traditional information management systems. Indeed, BDA infrastructures may improve communication between different units of large organizations, helping them respond to issues and opportunities in a timelier fashion (Rialti *et al.*, 2018).

5.2. Practical Implications

Given our findings, we suggest that large companies consider investing in BDA, particularly in developing BDA infrastructures that are flexible (Gupta & George, 2016). In fact, BDA infrastructures can create value only when they can ensure the flow of information over time without interruptions (Rialti *et al.*, 2018; Faraoni, Rialti, Zollo & Pellicelli, 2019). These infrastructures must be able to collect, store and analyze any kind of data in any situation. In addition, they must be inter-operable so they can ensure quality communication in the form of data sharing between the organization and its partners (Lu & Ramamurthy, 2011). Therefore, we also recommend that IT solutions such as data lakes be accessible to all partner organizations (Gupta and Giri, 2018). Data lakes are probably the best solution to making big data available to all. Cloud computing-based architectures (often on outsourced cloud computing platforms) are also a good possibility, because they prevent the organization from relying too heavily on internal systems (Hashem *et al.*, 2015). Artificial intelligence and machine learning may be capable of automatically extracting patterns from unstructured datasets without the need for human intervention (Waller & Fawcett, 2013; Chiang, 2018).

Nevertheless, managers should also focus on the people behind the scenes of the BDA infrastructures. The entire organization must embrace the notion of BDA. One method of accomplishing this goal is to promote the employees' creativity through competitions to solve BDA-related problems. Other methods include freeing them from having to follow extremely rigid procedures, and incentivizing their involvement in collaborative projects using the information management system (Cohen, Dolan, Dunlap, Hellerstein & Welton, 2009). We also advise top managers to drive and guide this transformation by empowering people who have strong problem-solving skills with regard to big data processes so they exploit its potentialities. Finally, putting together the right people who understand the problems with the right data is a formula for success (Ferraris *et al.,* 2018). Top managers should absorb this idea and try to build BDA-specific capabilities across all levels of their workforce.

By investing in BDA infrastructures as well as a specialized workforce, managers can promote the organization's ability to exploit big data. As a result, organizational ambidexterity, agility and improved performance may emerge as outcomes. By being able to exploit insights from manufacturers, customers and rivals, companies may find it easier to make the right decision at the right time, giving them a competitive edge. Finally, managers must lay the groundwork for this revolution by removing barriers to the implementation of BDA and understanding how the organizational processes, procedures and skills needed to collect and analyze big data are the “bricks” in building this new structure.

6. Limitations and Suggestions for Future Research

Despite the contributions our study makes to the literature, it still has several limitations. First, as in most survey-method based papers, the reports about the firm’s performance were self-reports and inferred from the managers’ personal responses (e.g. Santoro, Bresciani & Papa, 2018). In addition, we used data only from managers in the EU. Therefore, it is difficult to generalize our findings to other settings.

However, these limitations also create the opportunity for future studies. First, we believe there is still a need to explore the antecedents of organizational BDA capabilities. Other factors may matter in the relationship between BDA, ambidexterity, agility and performance. Second, it would be interesting to investigate the phenomenon using qualitative methods such as multiple case studies. Finally, we could test the same model using a sample of managers of small and medium-size companies to determine whether the factors and effects are similar to or different from those in larger organizations.

References

Akter, S., Wamba, S.F., Gunasekaran, A., Dubey, R., & Childe, S.J. (2016). How to improve firm performance using big data analytics capability and business strategy alignment?. *International Journal of Production Economics*, *182*, 113-131.

Arbuckle, J. (2013). *AMOS 22. User’s Guide. Chicago*. Chicago, IL: SmallWaters Corporation.

Armstrong, J.S., & Overton, T.S. (1977). Estimating nonresponse bias in mail surveys. *Journal of Marketing Research*, *14*(3), 396-402.

Bagozzi, R.P., & Yi, Y. (1988). On the evaluation of structural equation models. *Journal of the Academy of Marketing Science*, *16*(1), 74-94.

Baruch, Y. (1999). Response rate in academic studies—A comparative analysis. *Human Relations*, *52*(4), 421-438.

Bentler, P.M. (1990). Comparative fit indexes in structural models. *Psychological Bulletin*, *107*(2), 238-252.

Bloch, M., Blumberg, S. & Laartz, J. (2012). Delivering large-scale IT projects on time, on budget, and on value. McKinsey & Company Insights & Publications, October 2012.

Braganza, A., Brooks, L., Nepelski, D., Ali, M. & Moro, R. (2017). Resource management in big data initiatives: Processes and dynamic capabilities. *Journal of Business Research*, *70*, 328-337.

Bresciani, S., Ferraris, A., & Del Giudice, M. (2018). The management of organizational ambidexterity through alliances in a new context of analysis: Internet of Things (IoT) smart city projects. *Technological Forecasting and Social Change*, *136*, 331-338.

Cappellesso, G., & Thomé, K. M. (2019). Technological innovation in food supply chains: systematic literature review. *British Food Journal*, *121*(10), 2413-2428

Caputo, A., Marzi, G., & Pellegrini, M.M. (2016). The internet of things in manufacturing innovation processes: development and application of a conceptual framework. *Business Process Management Journal*, *22*(2), 383-402.

Cegarra-Navarro, J.G., Soto-Acosta, P., & Wensley, A.K. (2016). Structured knowledge processes and firm performance: The role of organizational agility. *Journal of Business Research*, *69*, 1544-1549.

Chen, H., Chiang, R.H., & Storey, V.C. (2012). Business intelligence and analytics: from big data to big impact. *MIS Quarterly*, *36*(4), 1165-1188.

Chiang, W.Y. (2018). Applying data mining for online CRM marketing strategy: An empirical case of coffee shop industry in Taiwan. *British Food Journal*, *120*(3), 665-675.

Cillo, V., Rialti, R., Del Giudice, M., Usai, A. (2019). Niche tourism destinations' online reputation management and competitiveness in big data era: evidence from three Italian cases. *Current Issues in Tourism*. DOI: https://doi.org/10.1080/13683500.2019.1608918.

Cohen, J., Dolan, B., Dunlap, M., Hellerstein, J. M., & Welton, C. (2009). MAD skills: new analysis practices for big data. *Proceedings of the VLDB Endowment*, *2*(2),1481-1492.

Davenport, T.H., Barth, P., Bean, R. (2012). How 'big data' is different. *MIT Sloan Management Review*, *54*, 43–46.

De Mauro, A., Greco, M., Grimaldi, M., & Ritala, P. (2018). Human resources for Big Data professions: A systematic classification of job roles and required skill sets. *Information Processing & Management*, *54*(5), 807-817.

Dubey, R., Gunasekaran, A., Childe, S. J., Papadopoulos, T., Luo, Z., Wamba, S. F., & Roubaud, D. (2017). Can big data and predictive analytics improve social and environmental sustainability? *Technological Forecasting and Social Change*, *144*, 534-545.

Eisenhardt, K.M., & Martin, J.A. (2000). Dynamic capabilities: what are they? *Strategic Management Journal*, *21*(10-11), 1105-1121.

Erevelles, S., Fukawa, N., & Swayne, L. (2016). Big Data consumer analytics and the transformation of marketing. *Journal of Business Research*, *69*, 897-904.

Faraoni, M., Rialti, R., Zollo, L., & Pellicelli, A.C. (2019). Exploring e-Loyalty Antecedents in B2C e-Commerce: Empirical results from Italian grocery retailers. *British Food Journal*, *121*(2), 574-589.

Ferraris, A., Mazzoleni, A., Devalle, A., & Couturier, J. (2018). Big data analytics capabilities and knowledge management: impact on firm performance. *Management Decision*, *58*(8), 1923-1936.

Field, A. (2013). *Discovering statistics using IBM SPSS statistics*. SAGE, London.

Franke, G.R. (2010). Multicollinearity. *Wiley International Encyclopedia of Marketing*, John Wiley and Sons.

Gibson, C.B., & Birkinshaw, J. (2004). The antecedents, consequences, and mediating role of organizational ambidexterity. *Academy of Management Journal*, *47*(2), 209-226.

Gölgeci, I., Ferraris, A., Arslan, A., & Tarba, S. Y. (2019). European MNE subsidiaries' embeddedness and innovation performance: Moderating role of external search depth and breadth. *Journal of Business Research*, *102*, 97-108.

Grefen, P., Rinderle-Ma, S., Dustdar, S., Fdhila, W., Mending, J., & Schulte, S. (2018). Charting Process-Based Collaboration Support in Agile Business Networks: Aligning the Need for a Dynamic Internet of Processes from Industry and Research Perspectives. *IEEE Internet Computing*, *22*(3), 48-57.

Gunasekaran, A., Yusuf, Y.Y., Adeleye, E.O., Papadopoulos, T. (2018). Agile manufacturing practices: the role of big data and business analytics with multiple case studies. *International Journal of Production Research*, *56*(1-2), 385-397.

Gupta, M., George, J.F. (2016). Toward the development of a big data analytics capability. *Information & Management*, *53*(8), 1049-1064.

Gupta S., & Giri V. (2018). Ensure High Availability of Data Lake. In Gupta, S. and V. Giri, *Practical Enterprise Data Lake Insights* (pp. 261-295), Berkeley (CA): Apress.

Hashem, I.A.T., Yaqoob, I., Anuar, N.B., Mokhtar, S., Gani, A., & Khan, S.U. (2015). The rise of “big data” on cloud computing: Review and open research issues. *Information Systems*, *47*, 98-115.

Hayes, A.F. (2013). *Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach*. Guilford Press, New York, NY.

Henderson, J.C., & Venkatraman, N. (1993). Strategic alignment: leveraging information technology for transforming organizations. *IBM Systems Journal*, *32*(1), 4-16.

Hofacker, C.F., Malthouse, E.C., & Sultan, F. (2016). Big data and consumer behavior: Imminent opportunities. *Journal of Consumer Marketing*, *33*(2), 89-97.

Hong, K.K., & Kim, Y.G. (2002). The critical success factors for ERP implementation: an organizational fit perspective. *Information & Management*, *40*(1), 25-40.

Iivari, J. (1992). The organizational fit of information systems. *Journal of Information Systems*, *2*, 3-29.

Jansen, J.J., Tempelaar, M.P., Van den Bosch, F.A., & Volberda, H.W. (2009). Structural differentiation and ambidexterity: The mediating role of integration mechanisms. *Organization Science*, *20*(4), 797-811.

Johnson, J.S., Friend, S.B., & Lee, H.S. (2017). Big data facilitation, utilization, and monetization: Exploring the 3Vs in a new product development process. *Journal of Product Innovation Management*, *34*(5), 640-658.

Kanellis, P., Lycett, L., & Paul, R.J. (1999). Evaluating business information systems fit: from concept to practical application. *European Journal of Information Systems*, *8*, 65-76.

Khan, Z., & Vorley, T. (2017). Big data text analytics: an enabler of knowledge management. *Journal of Knowledge Management*, *21*(1), 18-34.

Kwon, O., Lee, N., & Shin, B. (2014). Data quality management, data usage experience and acquisition intention of big data analytics. *International Journal of Information Management*, *34*(3), 387-394.

Labrinidis, A., & Jagadish, H.V., 2012. Challenges and opportunities with big data. *Proceedings of the VLDB Endowment*, *5*(12), 2032-2033.

Laudano, M.C., Zollo, L., Ciappei, C., & Zampi, V. (2018). Entrepreneurial universities and women entrepreneurship: a cross-cultural study. *Management Decision*. DOI: 10.1108/MD-04-2018-0391.

LaValle, S., Lesser, E., Shockley, R., Hopkins, M.S., & Kruschwitz, N. (2011). Big data, analytics and the path from insights to value. *MIT Sloan Management Review*, *52*(2), 21-44.

Lee, O.K., Sambamurthy, V., Lim, K.H., Wei, & K.K. (2015). How does IT ambidexterity impact organizational agility?. *Information Systems Research*, *26*(2), 398-417.

Lu, Y., & Ramamurthy, K. (2011). Understanding the link between information technology capability and organizational agility: An empirical examination. *MIS Quarterly*, *35*(4), 931-954.

Manyika, J., Chui, M., Brown, B., Bughin, J., Dobbs, R., Roxburgh, C., & Byers, A.H. (2011). Big data: The next frontier for innovation, competition, and productivity. *McKinsey Global Institute* (http://www.mckinsey.com/insights/mgi/research/technology_and_innovation/big_data_the_next_frontier_for_innovation; accessed August 4, 2018.

McAfee, A. & Brynjolfsson, E. (2012). Big data: the management revolution. *Harvard Business Review*, *90*(10), 60-68.

Melville, N., Kraemer, K., & Gurbaxani, V. (2004.) Information technology and organizational performance: An integrative model of IT business value. *MIS Quarterly*, *28*(2), 283-322.

Mikalef, P,. & Pateli, A. (2017). Information technology-enabled dynamic capabilities and their indirect effect on competitive performance: Findings from PLS-SEM and fsQCA. *Journal of Business Research*, *70*, 1-16.

Nunnally, J.C., 1978. *Psychometric Theory*. New York, NY: McGraw Hill.

O'Reilly III, C.A., & Tushman, M.L. (2008). Ambidexterity as a dynamic capability: Resolving the innovator's dilemma. *Research in Organizational Behavior*, *28*, 185-206.

Pandey, S.C., & Dutta, A. (2013). Role of knowledge infrastructure capabilities in knowledge management. *Journal of Knowledge management*, *17*(3), 435-453.

Pauleen, D.J., & Wang, W.Y. (2017). Does big data mean big knowledge? KM perspectives on big data and analytics. *Journal of Knowledge Management*, *21*(1), 1-6.

Picón, A., Castro, I., & Roldán, J. L. (2014). The relationship between satisfaction and loyalty: A mediator analysis. *Journal of Business Research*, *67*, 746-751.

Podsakoff, P.M., MacKenzie, S.B., Lee, J.Y., & Podsakoff, N.P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*(5), 879-898.

Preacher, K.J., & Hayes, A.F. (2004.) SPSS and SAS procedures for estimating indirect effects in simple mediation models. *Behavior Research Methods, Instruments, & Computers*, *36*(4), 717-731.

Prescott, M., (2014(. Big data and competitive advantage at Nielsen. *Management Decision*, *52*(3), 573-601.

Provost, F., & Fawcett, T. (2013). Data science and its relationship to big data and data-driven decision making, *Big Data*, *1*(1), 51-59.

Rafferty, A.E., & Jimmieson, N.L. (2017). Subjective perceptions of organizational change and employee resistance to change: Direct and mediated relationships with employee well-being. *British Journal of Management*, *28*(2), 248-264.

Raguseo, E., & Vitari, C. (2018). Investments in big data analytics and firm performance: an empirical investigation of direct and mediating effects. *International Journal of Production Research*, *56*(15), 5206-5221.

Raisch, S., & Birkinshaw, J. (2008). Organizational ambidexterity: Antecedents, outcomes, and moderators, *Journal of Management*, *34*(3), 375-409.

Rialti, R., Zollo, L., Pellegrini, M.M., & Ciappei, C. (2017). Exploring the antecedents of brand loyalty and electronic word of mouth in social-media-based brand communities: do gender differences matter?. *Journal of Global Marketing*, *30*(3), 147-160.

Rialti, R., Marzi, G., Silic, M., & Ciappei, C. (2018). Ambidextrous organization and agility in big data era: the role of business process management systems. *Business Process Management Journal*, 24 (5), 1091-1109.

Rialti, R., Marzi, G., Ciappei, C., & Busso, D. (2019). Big data and dynamic capabilities: a bibliometric analysis and systematic literature review. *Management Decision*, *57*(8), 2052-2068.

Roßmann, B., Canzaniello, A., von der Gracht, H., & Hartmann, E. (2018). The future and social impact of Big Data Analytics in Supply Chain Management: Results from a Delphi study. *Technological Forecasting and Social Change*, *130*, 135-149.

Santoro, G., Fiano, F., Bertoldi, B., & Ciampi, F. (2018). Big data for business management in the retail industry. *Management Decision*, *58*(8), 1980-1992.

Santoro, G., Bresciani, S., & Papa, A. (2018). Collaborative modes with cultural and creative industries and innovation performance: the moderating role of heterogeneous sources of knowledge and absorptive capacity. *Technovation*, DOI: https://doi.org/10.1016/j.technovation.2018.06.003

Scuotto, V., Ferraris, A., & Bresciani, S. (2016). Internet of Things: Applications and challenges in smart cities: a case study of IBM smart city projects. *Business Process Management Journal*, *22*(2), 357-367.

Soto-Acosta, P., & Cegarra-Navarro, J.G. (2016). New ICTs for knowledge management in organizations. *Journal of Knowledge Management*, *20*(3), 417-422.

Soto-Acosta, P., Popa, S., & Martinez-Conesa, I. (2018). Information technology, knowledge management and environmental dynamism as drivers of innovation ambidexterity: a study in SMEs. *Journal of Knowledge Management*, *22*(4), 824-849.

Tallon, P.P., & Pinsonneault, A. (2011). Competing perspectives on the link between strategic information technology alignment and organizational agility: insights from a mediation model. *MIS Quarterly*, *35*(2), 463-486.

Tan, K. H., Zhan, Y., Ji, G., Ye, F., & Chang, C. (2015). Harvesting big data to enhance supply chain innovation capabilities: An analytic infrastructure based on deduction graph. *International Journal of Production Economics*, *165*, 223-233.

Tarafdar, M., & Qrunfleh, S. (2017). Agile supply chain strategy and supply chain performance: complementary roles of supply chain practices and information systems capability for agility. *International Journal of Production Research*, *55*(4), 925-938.

Teece, D., Peteraf, M., & Leih, S. (2016). Dynamic capabilities and organizational agility: Risk, uncertainty, and strategy in the innovation economy. *California Management Review*, *58*(4), 13-35.

Teece, D.J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, *18*(7), 509-533.

Waller, M.A., & Fawcett, S.E. (2013). Data science, predictive analytics, and big data: a revolution that will transform supply chain design and management. *Journal of Business Logistics*, *34*(2), 77-84.

Wamba, S.F., Gunasekaran, A., Akter, S., Ren, S.J.F., Dubey, R., & Childe, S.J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. *Journal of Business Research*, *70*, 356-365.

Wamba, S.F., & Mishra, D. (2017). Big data integration with business processes: a literature review. *Business Process Management Journal*, *23*(3), 477-492.

Wang, G., Gunasekaran, A., Ngai, E.W., & Papadopoulos, T. (2016). Big data analytics in logistics and supply chain management: Certain investigations for research and applications. *International Journal of Production Economics*, *176*, 98-110.

Wang, Y., Kung, L., & Byrd, T.A. (2018). Big data analytics: Understanding its capabilities and potential benefits for healthcare organizations. *Technological Forecasting and Social Change*, *126*, 3-13.

Weber, Y., & Tarba, S.Y. (2014). Strategic Agility: A State of the Art Introduction to the Special Section on Strategic Agility. *California Management Review*, *56*(3), 5-12.

Yi, X., Liu, F., Liu, J., & Jin, H., (2014). Building a network highway for big data: architecture and challenges. *IEEE Network*, *28*(4), 5-13.

Zollo, L., Faldetta, G., Pellegrini, M.M., & Ciappei, C. (2017). Reciprocity and gift-giving logic in NPOs. *Journal of Managerial Psychology*, *32*(7), 513-526.

Zollo, L., Laudano, M.C., Boccardi, A., & Ciappei, C. (2019). From governance to organizational effectiveness: the role of organizational identity and volunteers' commitment. *Journal of Management and Governance*, *23*(1), 111-137.

Zollo, L., Yoon, S., Rialti, R., & Ciappei, C. (2018). Ethical consumption and consumers' decision making: the role of moral intuition. *Management Decision*, *56*(3), 692-710.

Highlights

- Big data and big data analytics (BDA) hold the power to revolutionize traditional ways of doing business;
- Ambidexterity and agility mediate the relationship between organizational BDA capabilities and performance;
- Organizational resistance to information system (IS) implementation and IS-organizational fit play a moderator role.

Big Data Analytics Capabilities and Performance: Evidence from a Moderated Multi-Mediation Model

Abstract

Big data analytics (BDA) have the power to revolutionize traditional ways of doing business. Nevertheless, the impact of BDA capabilities on a firm's performance is still not fully understood. These capabilities relate to the flexibility of the BDA infrastructure and the skills of the management and the firm's personnel. Most scholars explored the phenomenon from either a theoretical standpoint or neglected intermediate factors, such as organizational traits. This article builds on the dynamic capabilities view to propose and empirically test a model exploring whether organizational ambidexterity and agility mediate the relationship between BDA capabilities and organizational performance. Using data from surveys of 259 managers of large European organizations, we tested a proposed model using bootstrapped moderated mediation analysis. We found that organizational BDA capabilities affect a firm's ambidexterity and agility, which, in turn, affect its performance. These results establish ambidexterity and agility as positive mediators in the relationship between organizational BDA capabilities and a firm's performance. Furthermore, the organizational resistance to the implementation of information management systems and the fit between the organization and these systems also moderated this relationship. Practical implications for managers are also discussed.

Keywords: *Agility, Ambidexterity, Big Data, Big Data Analytics (BDA), Management Information Systems, Organizational Performance.*

1. Introduction

The emergence of big data has revolutionized old business models (McAfee & Brynjolfsson, 2012) as well as the management of organizational knowledge (Pauleen & Wang, 2017; Khan & Vorley, 2017). Big data are large, heterogeneous datasets containing different types and quantities of information (Manyika, Chui, Brown, Bughin, Dobbs, Roxburgh & Byers, 2011). Thanks to big data, managers today may know their organizations, their competitors and their customers better than ever (Dubey, Gunasekaran, Childe, Papadopoulos, Luo, Wamba, & Roubaud, 2017; Wang, Kung, & Byrd, 2018). Specifically, big data allows managers to monitor the status of each internal process, the performance of business units, processes and assets, as well as bottlenecks in the supply chain in real time (Akter, Wamba, Gunasekaran, Dubey & Childe, 2016; Roßmann, Canzaniello, von der Gracht, & Hartmann, 2018; Cappellesso & Thomé, 2019). Big data can also access new and updated data from the Internet to identify potential maneuvers by competitors (Erevelles, Fukawa & Swayne, 2016; Scuotto, Ferraris & Bresciani, 2016). In addition, big data can provide producers with information about their customers' behavioral patterns, requests and complaints (Hofacker, Malthouse & Sultan, 2016), both on the aggregate level, in the form of information about their customer base, and on the individual level, in the form of details about the individual customer's behavior over time.

Given the diffusion of big data, companies need to develop organizational big data analytics capabilities (or BDA) to extract relevant information and make sense of it to make decisions. Organizational BDA capabilities are an ensemble of capabilities that include infrastructure flexibility, management capabilities and personnel capabilities (Wamba, Gunasekaran, Akter, Ren, Dubey & Childe, 2017). Organizations that promote their BDA capabilities may have several different outcomes. Nevertheless, most of the existing literature agrees that BDA capabilities could influence organizations' economic performance. For example, Erevelles *et al.* (2016) pointed out how BDA capabilities may impact an organization's marketing capabilities and ability to react in a timely fashion to develop new marketing strategies. Their study showed how an organization's performance could improve as a result of new information about customers. In contrast, Tan, Zhan, Ji, Ye & Chang

(2015) and Wang *et al.* (2018) demonstrated how BDA capabilities have the power to revolutionize the management of the supply chain. Similarly, Kwon, Lee & Shin (2014) stressed how BDA could improve internal operations and processes, including organizational efficiency (Rialti, Marzi, Ciappei & Busso, 2019). Wamba *et al.* (2017) also observed how BDA capabilities could affect dynamic capabilities. Therefore, information from big data can impact an organization's performance by influencing its capability and adaptability. Large organizations benefit the most from data and BDA because they are well-positioned to put it to use (Prescott, 2014; Wamba & Mishra, 2017; Wamba *et al.*, 2017).

Notwithstanding the evidence about the impact of BDA, some gaps still exist in this stream of literature. Indeed, scholars have just begun to understand the complex relationships between the development of BDA and organizational performance. On one hand, part of the research is still theoretical (i.e., Rialti, Marzi, Silic & Ciappei, 2018) or at most qualitative (i.e., Cillo, Rialti, Del Giudice & Usai, 2019; Santoro, Fiano, Bertoldi & Ciampi, 2018). On the other hand, quantitative research on BDA capabilities and performance is still in its infancy (Dubey *et al.*, 2017; Wamba *et al.*, 2017). There is a clear need to explore which organizational traits could be influenced by BDA capabilities and their effect on performance. In addition, we also must identify the factors that prevent the successful implementation of BDA within organizations. This is the research gap we aim to fill with this paper.

Our goal is to propose and empirically test several hypotheses about the factors that affect the relationship between big data and organizational performance. We use a dataset derived from a survey conducted among 259 managers of large organizations involved in big-data projects to assess the effect of two mediators (ambidexterity and agility) and two moderators (organizational resistance to the implementation of information management systems and the fit between such systems and the organization) to conduct the test. We decided to focus only on large organizations because they are the major consumers and beneficiaries of big data (De Mauro, Greco, Grimaldi & Ritala, 2018).

Additionally, BDA capabilities require major investments that can be made only by large organizations (Cillo *et al.*, 2019; Gölgeci, Ferraris, Arslan & Tarba*,* 2019).

The research contributes to the existing literature in multiple ways. First, it reveals how information coming from big data could influence a firm's economic results, highlighting the role of organizational ambidexterity and agility in this relationship. Demonstrating this impact also underscores the importance of BDA in the achievement of ambidexterity—the ability to adapt to changes by using existing resources—as well as the importance of agility. Second, the study proposes and empirically tests an original moderated multi-mediation model that provides a better understanding of the complex interrelationships among the factors that allow companies to gain a competitive advantage from big data. Third, we highlight how organizational characteristics may prevent the successful application of big data by investigating the relevance of the fit between the organization and its information management system and the resistance to the implementation of such systems with regard to BDA-related projects. The findings demonstrate the expected results of investing in BDA and provide practical guidelines that companies can use to develop their BDA capabilities.

The paper is organized as follows. The following section includes a review of the existing literature on BDA, organizational BDA capabilities, and the potential effects of big data and BDA on a firm's performance. In addition, it also explains the interconnections among BDA, ambidexterity, agility, and performance. Building on this literature, we developed a model with nine hypotheses. The third section deals with the sampling procedure and the explanation of the methodological process. We used Hayes' multi-level mediation SPSS macro (2013) as the main method to analyze the collected data. We chose this method because, as a nonparametric resampling strategy, it requires no assumption of normality, it estimates indirect and interactive effects, its confidence intervals are very accurate, and it provides an effective test of the model's predictive validity. The fourth section reports the main results related to the mediators and moderators. Section five discusses these results, along with their implications. The last section describes the limitations of the study and provides suggestions for future research.

2.Theoretical Background and Development of Hypotheses

2.1. BDA Capabilities in Large Organizations

Big data differ from traditional datasets such as those in Excel files in at least seven ways: volume, velocity, variety, veracity, value, variability and visualization. Therefore, the term "big data" has frequently been used to describe datasets that are both large and complex, and cannot be analyzed with traditional statistical models (Manyika *et al.*, 2011).

Given these differences, big data management poses several significant challenges to organizations. To utilize this information, they must develop "big data architectures," which are networks composed of several processors, machines and databases that can collect, process, store and analyze big data (Yi, Liu, Liu & Jin, 2014). Such architectures need to be based on data lakes, which are systems or repository of data stored in their original format. A data lake is usually a single store of all enterprise data including raw copies of source system data and transformed data, derived from sensors monitoring machines or internal process (Gupta & Giri, 2018). Next, organizations may need to rely on nested computer networks capable of processing different kinds of data simultaneously. Such networks need to be based on open-source software capable of parallel computing and able to ensure inter-organizational operability. These characteristics allow organizations to collect, categorize, store and analyze data stored in repositories (Labrinidis & Jagadish, 2012). These architectures must be agile enough to adapt to changing organizational structures (Rialti *et al.*, 2018).

However, the machinery alone is insufficient for dealing with the complexity of big data management. Organizations must invest in hiring and training professionals for this task (Wamba *et al.*, 2017). For instance, big data analysts, scientists and engineers need to be skilled in R, Python, Hadoop, Not Only SQL (NoSQL) data models, schema-less data retrieval, and other tools that use artificial intelligence paradigms (LaValle, Lesser, Shockley, Hopkins & Kruschwitz, 2011). Hence, simple personnel re-training may not be sufficient to meet the challenges of big data. Indeed, the entire culture of the organization should be transformed according to the paradigms of the so-called "big data culture" (Tallon & Pinsonneault, 2011). In this culture, decisions are data driven, and employees should not be afraid to rely exclusively, or almost exclusively, on machines and data when making business-related decisions (Rialti *et al.*, 2019). Consequently, managers' resistance to computer-aided decision-making should be reduced to reap the advantages of big data (Akter *et al.*, 2016).

In addition to these main requirements, Wamba *et al.* (2017) outlined the notion of organizational BDA capabilities, which are an ensemble of capabilities related to the "ability to mobilize and deploy BDA-based resources in combination with other resources and capabilities" (p. 357). The authors highlighted three capabilities that are fundamental for any organization: the flexibility of the BDA infrastructure, BDA management capabilities and BDA personnel capabilities. BDA infrastructures, which are the ensemble of information systems capable of collecting, storing, processing and analyzing big data, should be able to adapt themselves to different types of data. This capability is fundamental to ensuring that technologies will be able to process different data flows and formats in any situation (Rialti *et al.*, 2018). BDA managerial capabilities are critical with regard to selecting and implementing the right BDA infrastructure and identifying the right information to extract from the datasets (Ferraris, Mazzoleni, Devalle & Couturier, 2018). Managers should be able to decide which technical solution is the best for their organization. Similarly, they need to have enough data analytics skills to make the right decisions when new data become available (Provost & Fawcett, 2013).

Finally, the personnel should also be skilled in BDA for several reasons. First, the presence of people with such skills reduces the likelihood of the organization's rejecting BDA or resisting the implementation of new information management systems and improves the functioning of the BDA infrastructure. Additionally, since employees are often those analyzing the data, they need the skills to identify the right data to be analyzed (Wamba *et al.*, 2017) and draw appropriate conclusions from their assessments. The literature indicates that these capabilities may create a competitive advantage for any organization (McAfee & Brynjolfsson, 2012).

As previously noted, in order for organizations to leverage the benefits of BDA, they must make significant investments. Therefore, small and medium-size businesses usually lack the capability to invest in systems such as parallel computing and data lakes (Raguseo & Vitari, 2018) or hire or re-train the necessary personnel. Thus, it is generally only large companies that can reap the benefits of BDA. Examples include the report of Davenport, Barth & Bean (2012) about how large organizations utilizing the Internet of Things and BDA can make their productive processes more efficient. Similarly, Hofacker *et al.* (2016) pointed out how big data could help retailers improve the customers' overall experience. Johnson, Friend & Lee (2017) and Rialti *et al.* (2018) assessed how BDA helps large organizations identify opportunities. Finally, Braganza, Brooks, Nepelski, Ali & Moro (2017) noted how BDA helps large organizations utilize their existing resources to exploit new opportunities.

2.2. Organizational BDA Capabilities, Ambidexterity and Performance

As highlighted in the previous section, organizational BDA capabilities are related to a structural aspect, the BDA infrastructure, as well as to HR management and organizational dynamics. Personnel and managerial BDA capabilities relate to organizational routines. Therefore, it is understandable that existing studies on BDA have used dynamic capabilities as their main theoretical approach (Akter *et al.*, 2016; Wamba *et al.*, 2017). Teece, Pisano, & Shuen (1997) coined the term "dynamic capabilities" to refer to an organization's ability to adapt to the changing environment in an adequate and timely fashion by reconfiguring internal or external processes and resources based on existing competencies. While some definitions link dynamic capabilities to organizational improvisation, they actually consist of "identifiable and specific routines" (Eisenhardt & Martin, 2000, p. 1107). Indeed, some organizational routines and processes are capable of diffusing into the best practices within an organization.

According to Eisenhardt and Martin (2000), organizational routines may be broken down into smaller routines or processes that are the "bricks" forming a complete routine or process. In particular, the standalone routines that derive from BDA managerial and personnel practices may represent bricks that can be utilized in different situations, thus creating a competitive advantage for an organization (Braganza *et al.*, 2017). Given that BDA infrastructures are usually extremely flexible, inter-operable, scalable, and capable of adapting to different kinds of data from different contexts, they are also capable of ensuring the flow of information over time and in any situation (Rialti *et al.*, 2018). It is then clear how BDA and BDA capabilities may influence a firm's performance (Wamba *et al.*, 2017). Such outcomes also accord with studies assessing how information management systems such as BDA (Bloch, Blumberg & Laartz, 2012) create value (Melville, Kraemer & Gurbaxani, 2004).

Research has also established that dynamic capabilities can have a positive effect on a firm's performance because they are indicative of a greater degree of organizational ambidexterity (O'Reilly & Tushman, 2008). Organizations that can re-arrange existing resources and routines to address new problems are also better able to identify changes in the environment and exploit opportunities. Dynamic capabilities related to BDA capabilities could improve their ability to identify new opportunities and threats. Information extracted thanks to BDA allows businesses to identify new opportunities and benefit from them (Rialti *et al.*, 2018). According to the same reasoning, information management systems that can adapt to different situations and data may also help firms identify and exploit new opportunities (Lu & Ramamurthy, 2011). Consequently, given that ambidexterity may influence performance, it may represent an intermediate variable between organizational BDA capabilities and a firm's performance. Thus, we propose the following hypotheses:

H1: *Organizational BDA capabilities are positively related to superior performance*.

H2: *Organizational BDA capabilities are positively related to a firm's ambidexterity.*

H3: *Ambidexterity is positively related to superior performance. Hence, ambidexterity mediates the relationship between organizational BDA capabilities and a firm's performance.*

2.3. Organizational BDA Capabilities, Agility and Performance

Organizational agility, meaning the ability of a business to renew itself and react quickly when necessary (Teece, Peteraf & Leih, 2016), derives directly from a firm's ability to adapt existing assets to new situations. Indeed, agility is often connected to an organization's dynamic capabilities. In cases in which the architectures and procedures required to process information do not represent a burden to an organization's dynamism, its agility may increase significantly (Tarafdar & Qrunfleh, 2017). Such a phenomenon is linked to the fact that abundant information flowing freely within an organization could make people aware of what needs to be done. These findings also emerged in the literature exploring the importance of BDA capabilities (Rialti *et al.*, 2019). Specifically, researchers have noted that, thanks to information extracted by BDA infrastructures, managers and personnel with strong BDA skills can make quicker decisions, which may affect an organization's ability to react (McAfee & Brynjolfsson, 2012; Wamba & Mishra, 2017). These results demonstrate how organizational BDA capabilities influence a firm's agility (Lu & Ramamurthy, 2011). In addition, agility is frequently associated with better organizational performance, showing how an adaptable and agile organization can thrive even in difficult times. Thus, we posit that:

H4: *Organizational BDA capabilities are positively related to agility.*

H5: *Agility is positively related to superior performance. Hence, agility mediates the relationship between organizational BDA capabilities and a firm's performance.*

2.4. Ambidexterity and Agility

As noted earlier, ambidexterity "is vital to pursue both […] exploration and exploitation for its innovative redesign of operational processes and continuous productivity improvement simultaneously” (Lee, Sambamurthy, Lim & Wei., 2015, p. 402). Studies have established that ambidexterity is related to the improved ability of a firm to respond effectively to market changes and is an antecedent of agility. Improving a firm’s exploitation and exploration capabilities may prompt and promote its reconfiguration and responsiveness, which are two distinguishing characteristics of agile organizations (Lee *et al.*, 2015). In the big data era, researchers have established that companies that utilize advanced IT systems that foster ambidexterity can become agile because information may make internal operations more efficient and streamlined. Thus, we hypothesize that:

H6: *Organizational ambidexterity is a critical antecedent of agility.*

2.5. Moderators from the information management system literature

The components of BDA infrastructures share the same theoretical foundation as any other management information system. BDA infrastructures are fundamental for decision-making, for the coordination, control and analysis of processes, and for the visualization of information. These elements accord with the definition of information management systems (Chen, Chiang & Storey, 2012). The implementation of BDA infrastructures and that of information management systems may have similar dynamics, making it possible to identify the same antecedents. Researchers have established that the better the alignment between an information management system and an organization’s characteristics is, the stronger the effect of the information management system (Iivari, 1992; Kanellis, Lycett & Paul, 1999). Specifically, the information management system’s functionalities must be aligned with the scope of the organization (Henderson & Venkatraman, 1993; Pandey & Dutta, 2013). Similarly, there must also be an alignment between the users’ capacities and the system’s characteristics, between the data that the system should process and the data existing within the organization’s datasets, and between the existing procedures and the new ones that will exist after the implementation of the information management system (Hong & Kim, 2002). Thus, the development of BDA capabilities is related to the fit between such new capabilities and those already existing within an organization.

Another factor of importance in the development of BDA capabilities is how resistant an organization is to change. If existing IT infrastructures are totally incompatible with BDA, managers do not want to make computer-aided decisions, and employees are incapable of running the systems, it may be impossible to develop BDA. These issues are consistent with the research on organizational resistance to change (Rafferty & Jimmieson, 2017). Thus, we propose that:

H7 a, b, c: *The fit between the organization and the information management system may positively moderate the relationships between organizational BDA capabilities and (a) ambidexterity, (b) agility or (c) performance.*

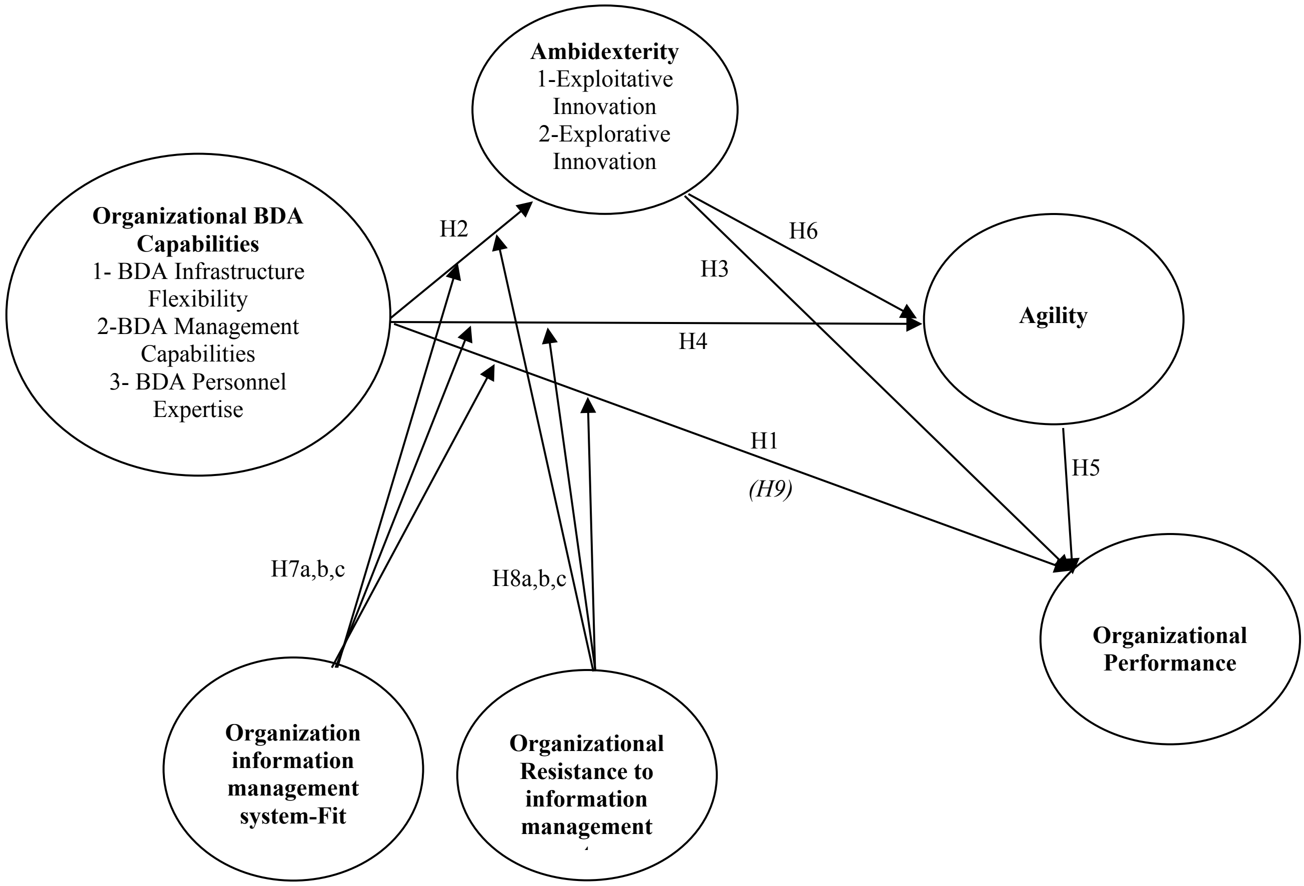
H8 a, b, c: *Organizational resistance to the implementation of an information management system may negatively moderate the relationship between BDA capabilities and (a) ambidexterity, (b) agility or (c) performance.*

2.6. Conceptual Model

Building on the previous hypotheses, the authors developed the conceptual model proposed in Figure 1 with several mediators and moderators. The final model consists of 9 hypotheses. Indeed, the main objective of this research is to investigate how organizational ambidexterity and agility may mediate the relationship between organizational BDA capabilities and performance. Such a complex model is justified by the necessity to develop a model including all the direct effect and the mediated effects between all the variables. The authors also included in the analysis the final hypothesis concerning the direct relationship between organizational BDA capabilities and performance.

H9*: The relationship between organizational BDA capabilities and performance is mediated by ambidexterity and agility.*

Figure 1 - Hypothesized Model



Notes:
H7 indicates the moderating effect of the fit between an organization and the information management system
H8 indicates the moderating effect of the organization's resistance
H9 indicates the multi-mediation hypothesis (the mediating effect of ambidexterity and agility on BDA → the relationship with the firm's performance)

Source. Authors' Elaboration

3. Method

3.1 Sampling

To test our hypotheses, we used data from a sample of European managers collected with the help of a UK-based marketing research company. The company that was contacted to collect the data owns a database containing information from about 10,000 UK, EU and US managers. Among these, about 8,500 of them are either from the UK or the EU and have managerial roles in what the EU defines as large organizations. Additional screening criteria were used to create the final pool of potential respondents, including 1) employment status (full time, part-time); 2) role within the organization (partner, managing director, senior manager, middle manager, junior manager); 3) expertise in big data (expert level); 4) leadership position (having more than two direct subordinates); 5) industry (agriculture, adult/college education, broadcasting, computer/electronic, construction, design/industrial design, electricity/oil and gas, finance/insurance, hotel and tourism, information/data processing/communication, marketing, marketing research, military, mining, product development, publishing, retail and wholesale, scientific/technical services, software/software development, pharmacy/healthcare in general, telecommunication) and organization's typology (large private, publicly listed).

In the end, the survey was administered to a sample composed of 862 managers. We received 259 completed questionnaires in the period between September and December 2018. This response rate of 30.04% accords with the usual response rate for surveys from managers (Baruch, 1999). Among the respondents, 125 were men (48.3%), and 134 (51.7%) were women. As reported in Table 1, most of them (49%) had more than 10 years of experience with information management systems.

To avoid non-response bias (Rogelberg & Stanton, 2007), in May 2018 we pretested the questionnaire by emailing a link to an electronic survey to seven scholars with a strong background in either information management systems or big data. We took this step to ensure that the survey was carefully structured, easy to complete, of an adequate length, and had clear and unambiguous questions (Laudano, Zollo, Ciappei & Zampi, 2018). After this pre-test, no modifications or corrections were made to the final questionnaire. We also evaluated the sample for potential non-response bias by conducting a wave analysis (Armstrong & Overton, 1977), which compared early (September-October 2018) and late (November-December 2018) respondents according to key variables such as age, gender, employment, and the dependent variables of our hypothesized model. The results of *t*-tests across such variables showed no significant differences between the early and late groups, thus indicating that non-response bias was not a concern.

Table 1 – Summary of the Sample's Characteristics

Control Variable	n	%
Gender		
Male	125	*48.3*
Female	134	*51.7*
Age		
18-24	30	*11.5*
25-29	45	*17.3*
30-39	105	*41*
40-49	55	*21.1*
More than 50	24	*9.2*
Education		
Primary school	1	*0.4*
Secondary school	19	*7.3*
High school	55	*21.2*
Bachelors' degree	122	*47.1*
Masters' degree	44	*17.0*
PhD	12	*4.6*
Other	6	*2.4*
Years of experience		
Less than 1 year	5	*1.9*
1-5 years	60	*23.2*
5-10 years	67	*25.9*
More than 10 years	127	*49.0*
Industry		
Adult/college education	2	*0.8*
Broadcasting	1	*0.4*
Computer/electronic	28	*11.2*
Electricity/oil and gas	8	*3.1*
Finance/insurance	20	*7.7*
Hotel and tourism	6	*2.3*
Information/data processing/communication	27	*10.4*
Manufacturing	16	*6.2*
Marketing	8	*3.1*
Marketing research	4	*1.5*
Retail and wholesale	31	*12*
Scientific/technical services	43	*16.6*
Pharmacy/healthcare in general	29	*12.2*
Telecommunication	14	*5.6*
Other	22	*6.9*
Organization's turnaround		
50-99 Million (€)	202	*78*
100 Million - 1 Billion (€)	33	*12.7*
More than 1 Billion (€)	24	*9.3*

Source: Authors' elaboration

3.2 Measures

The entire survey contained 83 items. We measured organizational BDA capabilities through the 49-item scale used by Wamba *et al.* (2017). In accordance with previous research, we considered organizational BDA capabilities a second-order variable (Gunasekeran, Yusuf, Adeleye &

Papadopoulos 2018; Mikalef & Pateli, 2017). The selected variables derived from three first-order variables, namely the flexibility of the BDA infrastructure (11 items), BDA management capabilities (21 items), and BDA personnel expertise (17 items).

Statements related to the flexibility of the BDA infrastructure included those related to connectivity (four items, such as “Compared to rivals within our industry, our organization has the foremost available analytics systems”), compatibility (three items, such as “Software applications can be easily used across multiple analytics platforms”) and modularity (four items, such as “Reusable software modules are widely used in new system development”) as latent variables.

Statements related to BDA management capabilities included those related to planning (four items, such as “We continuously examine innovative opportunities for the strategic use of business analytics”), decision-making (five items, such as “When we make business analytics investment decisions, we estimate the effect they will have on the productivity of the employees' work”), coordination (four items, such as “In our organization, business analysts and line people meet regularly to discuss important issues”) and control (eight items, such as “In our organization, the responsibility for analytics development is clear”) as latent variables.

Finally, statements related to BDA personnel expertise included those related to technical knowledge (five items, such as “Our analytics personnel are very capable in decision support systems (e.g., expert systems, artificial intelligence, data warehousing, mining, etc.)”), , business knowledge (four items, such as “Our analytics personnel are very capable in interpreting business problems and developing appropriate solutions”) and relational knowledge (four items, such as “Our analytics personnel work closely with customers and maintain productive user/client relationships”) as variables (Wamba *et al.,* 2017).

To measure organizational ambidexterity, we used the 8-item scale of Jansen, Tempelaar, Van den Bosch, & Volberda (2009). We followed the suggestion to consider ambidexterity as a standalone first-order variable. Therefore, we used the two latent variables – explorative innovation (i.e., “Our organization accepts demands that go beyond existing products and services”) and exploitative innovation (i.e., “We increase economies of scale in existing markets”) – to create the first-order organizational ambidexterity variable.

To measure organizational agility, we used Cegarra-Navarro, Soto-Acosta, & Wensley (2016) 6-item scale (i.e., “We have the ability to rapidly respond to customers' needs”). Previous researchers have used this scale successfully to explore the impact of information systems and technologies on organizational agility (Soto-Acosta & Cegarra-Navarro, 2016).

To measure organizational performance, we used Gibson & Birkinshaw’s (2004) 4-item scale (i.e., “The organization does a good job in satisfying our customers”).

Finally, we measured organizational resistance to the implementation of information management systems using Hong & Kim’s (2002) 5-item scale (i.e., “There have been many users resisting the BDA implementation”). We also used their 11-item scale to assess the fit between the organization and the information management system (i.e., “The processes built in BDA information systems meet all needs required from organizational processes”).

Respondents rated the items on a 7-point Likert scale ranging from 1=strongly disagree to 7=strongly agree.

4. Analysis and Results

4.1. Descriptive statistics and correlation analysis

The mean and standard deviation of all constructs along with the Pearson’s r values are reported in Table 2. The strongest correlation was between business knowledge and technical knowledge (r=0.807; p<0.01). The second strongest was between coordination and planning (r=0.805; p<0.01).

Table 2 - Correlation matrix

	Mean	*SD*	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*	*15*
1) Connectivity	4.37	1.62	*(0.768)*														
2) Compatibility	4.67	1.62	0.674*	*(0.842)*													
3) Modularity	4.14	1.53	0.655*	0.517*	*(0.752)*												
4) Planning	4.63	1.56	0.708*	0.656*	0.595*	*(0.887)*											
5) Decision making	4.84	1.53	0.594*	0.503*	0.624*	0.725*	*(0.844)*										
6) Coordination	4.56	1.61	0.544*	0.543*	0.520*	0.656*	0.600*	*(0.861)*									
7) Control	4.55	1.53	0.718*	0.705*	0.665*	0.805*	0.706*	0.764*	*(0.919)*								
8) Technical knowledge	4.78	1.48	0.632*	0.528*	0.616*	0.686*	0.676*	0.645*	0.777*	*(0.909)*							
9) Business knowledge	4.99	1.52	0.532*	0.581*	0.526*	0.693*	0.650*	0.655*	0.749*	0.757*	*(0.918)*						
10) Relational knowledge	4.89	1.52	0.577*	0.594*	0.556*	0.701*	0.654*	0.661*	0.745*	0.717*	0.807*	*(0.869)*					
11) Ambidexterity	4.63	1.65	0.575*	0.470*	0.551*	0.647*	0.609*	0.488*	0.623*	0.538*	0.496*	0.535*	*(0.842)*				
12) Agility	4.91	1.51	0.565*	0.586*	0.568*	0.622*	0.650*	0.625*	0.635*	0.560*	0.558*	0.545*	0.685	*(0.881)*			
13) Performance	4.74	1.37	0.642*	0.650*	0.625*	0.573*	0.550*	0.582*	0.538*	0.602*	0.633*	0.615*	0.519	0.599	*(0.852)*		
14) Resistance	4.05	1.55	0.280*	0.255*	0.185*	0.082	0.125*	0.082	0.189*	0.265*	0.250*	0.291*	0.301	0.222	0.093	*(0.940)*	
15) Fit	4.37	1.44	0.322*	0.350*	0.348*	0.403*	0.388*	0.425*	0.390*	0.428*	0.375*	0.440*	0.609	0.623	0.536	0.379	*(0.904)*

Notes:
** p-value < 0.01
Cronbach's Alpha reported on diagonal

Source: Authors' elaboration

To check for potential multicollinearity, we estimated the variance inflation factors (VIFs) (Lee *et al.,* 2016) using the SPSS collinearity test (Field, 2013). Each of the independent variables exhibited a VIF value below the threshold of 3.0 (Picón, Castro & Roldán, 2014), ranging from 1.50 to 2.80, with a mean of 2.35, thus indicating no problem with multicollinearity. Using the 0.80 benchmark for the strength of the correlations (Franke, 2010), as Table 4 shows, none of the variables were highly correlated. As a result, there were no multicollinearity concerns. Hence, all of the independent variables were included in the moderated mediation analysis.

4.2 Confirmatory factor analysis

A confirmatory factor analysis (CFA) was conducted using AMOS v. 22 (Arbuckle, 2013). The maximum likelihood function of AMOS was used to estimate parameters and test the hypothesized relationships among the variables (Bagozzi & Yi, 1988). We first estimated a measurement model to evaluate the goodness-of-fit indexes and confirm the parsimony of the hypothesized model (Bagozzi & Yi, 1988).

Concerning the absolute fit indexes, the $\chi2$ was significant ($\chi2 = 143.192$, $p<0.01$) and the relative $\chi2$ provided an acceptable fit with a *t*-test of $\chi2/df = 2.11$ (less than 3, as required) (Bagozzi & Yi, 1988; Bentler, 1990). Next, the global fit index (GFI) (0.995) suggested a satisfactory fit (higher than 0.9, as required). Finally, the root means square error of approximation (RMSEA) of 0.062 suggested an acceptable model fit, being less than 0.07, as required (Bentler, 1990).

Concerning the relative fit indexes, the most commonly used are the comparative fit index (CFI), the incremental fit index (IFI), the normed fit index (NFI), and the Tucker-Lewis index (TLI), also known as the non-normed fit index (Bagozzi & Yi, 1988). All of the relative fit indexes showed acceptable values, being higher than 0.9, as required. Specifically, CFI = 0.945; IFI = 0.930; NFI = 0.922; TLI = 0.938 (Bentler, 1990).

The CFA showed that all of the factor loadings – the path coefficients between the observed variables (indicators) and the latent variables – were significant ($p < 0.01$). To evaluate the internal consistency of the indicators, we estimated the composite reliability (CR) for each latent variable. CR values were all higher than 0.6, as required (Bagozzi & Yi, 1988). Moreover, the convergent validity was also assessed through the average variance extracted (AVE) of each latent variable (Zollo, Faldetta, Pellegrini & Ciappei, 2017; Zollo, Yoon, Rialti & Ciappei, 2018). All of the variables had an AVE value higher than 0.5, as required (Bentler, 1990).

Finally, we tested for the presence of common method bias by following the procedures suggested by Podsakoff, MacKenzie, Lee & Podsakoff (2003). First, we pretested the scales to eliminate items that were vague from the questionnaire. Second, we conducted Harman's one-factor test to determine if there was a single factor that explained most of the variance. Next, we utilized an AMOS corroborative factor examination to contrast the proposed model and a model that loaded all of the variables onto a single factor (Podsakoff *et al.*, 2003). The examination produced a noteworthy change in $\chi 2$, as required – the $\chi 2$ contrast test with one degree of freedom was 10, much higher than 3.84, which is the basic level related to p1⁄40.05 (Rialti, Zollo, Pellegrini & Ciappei, 2017; Zollo, Laudano, Boccardi & Ciappei, 2019). Our proposed model was a better fit than the one-factor model (Podsakoff *et al.*, 2003).

4.3. Testing the Hypotheses

We tested the moderated mediation hypotheses following the procedure proposed by Hayes and colleagues (Hayes, 2013; Preacher & Hayes, 2004) and using the SPSS PROCESS macro (v. 2.16). Specifically, to conduct a multiple mediation analysis (model 6 of PROCESS) and a moderation analysis (model 1 of PROCESS), we used the bootstrapping method (based on 5,000 bootstrap samples) and computed 95% bias-corrected lower level confidence intervals (LLCIs) and upper level confidence intervals (ULCIs) around the estimates of the indirect effects (Zollo *et al.,* 2019).

Independent variables such as organizational BDA capabilities should be significantly related to the mediation variables of ambidexterity and agility. After controlling for the effect of the independent variables, the mediation variables should also be significantly related to the dependent variable of performance. According to Hayes (2013), an important indication of mediation is the significance level of the *indirect* effect from organizational BDA capabilities (the "X" variable) to performance (the "Y" variable) through ambidexterity and agility (the "M" variables), as indicated by the *p*-value or the LLCIs and ULCIs. In other words, the *total* effect of organizational BDA capabilities on performance should differ from the *direct* effect of such a relationship, resulting in an *indirect* effect different from zero.

Concerning moderation, the hypothesized moderating variables (the "W" variables, such as the fit between the organization and the information management system and the organizational resistance to the implementation of information management systems) should have a significant effect ($p < 0.05$) on the previously assessed relationships (i.e., organizational BDA capabilities → ambidexterity) and thus modify the original regression weights, either in a positive way (positive moderation such as the fit between the organization and the information management system) or a negative way (negative moderation such as the organizational resistance to the implementation of information management systems). Results are reported in Table 3.

Concerning the mediation analysis, the total effect of organizational BDA capabilities on performance (without considering the mediating variables) was significant and high (β=+0.768; $p <$ 0.01), confirming *H1*. Our empirical evidence also showed that organizational BDA capabilities strongly impacted ambidexterity (β=+0.829; p<0.01), confirming *H2*. Similarly, both organizational BDA capabilities (β=+0.305; p<0.01) and ambidexterity (β=+0.644; p<0.01) had a positive effect on agility, providing statistical support for *H4* and *H6*. While ambidexterity had no significant effect on performance (p>0.10), agility had a positive impact on performance (β=+0.371; p<0.01). Hence, *H3* was not supported but *H5* was confirmed. Finally, the direct effect of organizational BDA capabilities on performance (considering the mediating variables) was significant but reduced (β=+0.586;

p<0.01), showing that ambidexterity and agility had a partial mediation effect. Specifically, the original influence of +0.768 was reduced to +0.586 due to the multi-mediation effect.

Table 3 – Bootstrapped moderated-mediation results

			β	***p***	***Hypothesis***	**(*LLCI; ULCI*)**	***R²***
Mediation:							
H1 - Organizational BDA Capabilities	→	Performance	+0.768	***	Supported	(0.656; 0.879)	45%
H2 - Organizational BDA Capabilities	→	Ambidexterity	+0.829	***	Supported	(0.739; 0.919)	56%
H3 - Ambidexterity	→	Performance	-	0.105	Not Supported	-	45%
H4 - Organizational BDA Capabilities	→	Agility	+0.305	***	Supported	(0.193; 0.745)	72%
H5 - Agility	→	Performance	+0.371	***	Supported	(0.189; 0.554)	45%
H6 - Ambidexterity	→	Agility	+0.644	***	Supported	(0.543; 0.745)	72%
H9 - Ambidexterity + Agility (Direct Effect)	→	BDA → Performance	+0.586	***	Supported	(0.412; 0.759)	42%
Moderation:							
H7a - Organization-Information Management System Fit	→	BDA → Ambidexterity	-	.~~645~~	Not Supported	-	57%
H7b - Organization-Information Management System Fit	→	BDA→Agility	+0.08	*	Supported	(0.036; 0.094)	56%
H7c - Organization-Information Management System Fit	→	BDA → Performance	+0.15	***	Supported	(0.079; 0.208)	46%
H8a - Resistance to Information Management System	→	BDA →Ambidexterity	-0.05	**	Supported	(-0.102; 0.002)	57%
H8b - Resistance to Information Management System	→	BDA → Agility	-	~~0.916~~	Not Supported	-	-
H8c - Resistance to Information Management System	→	BDA -> Performance	+0.14	***	Supported	(0.072; 0.197)	47%

***p-value < 0.01
** p-value < 0.01
* p-value < 0.01

β: regression weight estimate; ***p***: p-value; ***LLCI***: lower level of confidence interval; ***ULCI***: upper level of confidence interval; ***R²***: multiple squared correlation indicating the percentage of variance explained.

Source: Authors' Elaboration

With regard to the moderating variables, the fit between the organization and the information management system had no significant effect on the organizational BDA capabilities → ambidexterity relationship ($p > 0.10$). Therefore, *H7a* was rejected. Instead, the fit between the organization and the information management system positively moderated the organizational BDA capabilities→agility relationship (β=+0.08; p<0.10) and the organizational BDA capabilities→performance relationship (β=+0.15; p<0.01), providing statistical support for *H7b* and *H7c*, respectively. The organizational resistance to the implementation of information management systems had a negative moderating effect on the organizational BDA capabilities→ambidexterity relationship (β=-0.05; p<0.05), which supported *H8a*. However, it had no significant moderating effect on the organizational BDA capabilities→agility relationship (p>0.10). Therefore, *H8b* was rejected. Finally, the organizational resistance to the implementation of information management systems had a positive moderating effect on the organizational BDA capabilities→performance relationship (β=+0.14; p<0.01), which confirmed *H8c*.

5. Discussion and Managerial Implications

5.1. Theoretical Implications

The results of our analysis highlight how organizational BDA capabilities may re-shape the structure of large organizations. Specifically, we documented that the infrastructures, processes and skills to extract meaningful information from big data may allow large organizations to better identify and exploit opportunities in the markets (Wang, Gunasekaran, Ngai & Papadopoulos, 2016). The research provides various insights into the relationship between big data and a firm's performance.

The most important results from this study show how the organizational ambidexterity and agility derived from BDA capabilities have a positive effect on performance. The causes underlying this phenomenon are understandable, given that an organization capable of responding quickly to changes may outperform its rivals (Chen *et al.*, 2012). Scholars who have documented the value-generating potential of information for organizations and those analyzing the impact of big data using dynamic capabilities as their main theoretical lens have come to similar conclusions (Wamba *et al.*, 2017).

Our results also underscore the fact that a firm's ambidexterity and agility matter. Hence, the development and/or improvement in organizational BDA capabilities can help large organizations in their pursuit of ambidexterity (Raguseo & Vitari, 2018). This finding accords with previous research on organizational ambidexterity. Indeed, the more information an organization can obtain about the state of the market, the more it may be able to identify new opportunities and develop new strategies to exploit them (Raisch & Birkinshaw, 2008). As an organization becomes more capable of accomplishing these goals, it may also become more dynamic and responsive to changes. Ambidextrous organizations can develop new offerings in a shorter period of time and reorganize lean supply chains according to changes in customer demand (Weber & Tarba, 2014). This is particularly true if the ambidexterity derived from ad-hoc information systems allows a company to collect, process and distribute information from outside the organization to its internal members (Lee *et al.*, 2015).

Thus, our study enriches the literature about organizational BDA capabilities and a firm's performance by exploring how ambidexterity and agility can help organizations extract information from big data that they can use to improve their performance (Gupta & George, 2016; Rialti *et al.*, 2019; Wamba *et al.*, 2017). The findings also extend the literature on big data and dynamic capabilities (Akter *et al.*, 2016) by proposing a moderated multi-mediation model useful for understanding the complex dynamics and interrelationships in this context. Hence, organizational big data capabilities are related to broader dynamic capabilities and the ability of the organization to thrive in the competitive arena (Gunasekaran *et al.*, 2018). Our study also contributes to the existing literature about the organizational characteristics that prevent or promote the successful application of big data (Hashem, Yaqoob, Anuar, Mokhtar, Gani & Khan, 2015) by highlighting the different effects of organizational resistance to the implementation of information management systems and the fit between the organization and such systems. Information about these two factors should help researchers and practitioners assess whether an organization will succeed or fail in using big data.

Finally, the research is of value because it focuses on BDA outcomes specifically in large organizations. In such firms, the effects can be substantial, and large companies are those who may benefit the most from big data (McAfee & Brynjolfsson, 2012). Indeed, they are the only kinds of organizations equipped to invest in the infrastructure needed to analyze big data and leverage the results (De Mauro *et al.*, 2018).

Interestingly, BDA infrastructures, which are a constituent factor of BDA capabilities, promote the ambidexterity and agility of large organizations. This finding somewhat contradicts the common beliefs about information management systems (which BDA infrastructures are). In fact, the traditional literature has frequently stressed the fact that information management systems are usually based on rigid infrastructures that might hamper organizational dynamism (Soto-Acosta, Popa & Martinez-Conesa, 2018). One explanation for this discrepancy may be that, due to their technical characteristics, BDA infrastructures demonstrate better operating performance than traditional information management systems. BDA infrastructures - whether based on cloud computing, data lakes or the Internet of Things (Bresciani, Ferraris & Del Giudice, 2018; Caputo, Marzi & Pellegrini, 2016) - are actually based on leaner architectures than traditional information management systems. Another explanation may be that BDA infrastructures provide so much information to large organizations that they improve their ability to identify opportunities, exploit them, and respond dynamically to changes (Grefen, Rinderle-Ma, Dustdar, Fdhila, Mending & Schulte, 2018). Given that large organizations are usually characterized as more rigid and less nimble than small and medium-size businesses (De Mauro *et al.*, 2018), BDA infrastructures may provide a solution to this problem because they are less cumbersome than traditional information management systems. Indeed, BDA infrastructures may improve communication between different units of large organizations, helping them respond to issues and opportunities in a timelier fashion (Rialti *et al.*, 2018).

5.2. Practical Implications

Given our findings, we suggest that large companies consider investing in BDA, particularly in developing BDA infrastructures that are flexible (Gupta & George, 2016). In fact, BDA infrastructures can create value only when they can ensure the flow of information over time without interruptions (Rialti *et al.*, 2018; Faraoni, Rialti, Zollo & Pellicelli, 2019). These infrastructures must be able to collect, store and analyze any kind of data in any situation. In addition, they must be inter-operable so they can ensure quality communication in the form of data sharing between the organization and its partners (Lu & Ramamurthy, 2011). Therefore, we also recommend that IT solutions such as data lakes be accessible to all partner organizations (Gupta and Giri, 2018). Data lakes are probably the best solution to making big data available to all. Cloud computing-based architectures (often on outsourced cloud computing platforms) are also a good possibility, because they prevent the organization from relying too heavily on internal systems (Hashem *et al.*, 2015). Artificial intelligence and machine learning may be capable of automatically extracting patterns from unstructured datasets without the need for human intervention (Waller & Fawcett, 2013; Chiang, 2018).

Nevertheless, managers should also focus on the people behind the scenes of the BDA infrastructures. The entire organization must embrace the notion of BDA. One method of accomplishing this goal is to promote the employees' creativity through competitions to solve BDA-related problems. Other methods include freeing them from having to follow extremely rigid procedures, and incentivizing their involvement in collaborative projects using the information management system (Cohen, Dolan, Dunlap, Hellerstein & Welton, 2009). We also advise top managers to drive and guide this transformation by empowering people who have strong problem-solving skills with regard to big data processes so they exploit its potentialities. Finally, putting together the right people who understand the problems with the right data is a formula for success (Ferraris *et al.,* 2018). Top managers should absorb this idea and try to build BDA-specific capabilities across all levels of their workforce.

By investing in BDA infrastructures as well as a specialized workforce, managers can promote the organization's ability to exploit big data. As a result, organizational ambidexterity, agility and improved performance may emerge as outcomes. By being able to exploit insights from manufacturers, customers and rivals, companies may find it easier to make the right decision at the right time, giving them a competitive edge. Finally, managers must lay the groundwork for this revolution by removing barriers to the implementation of BDA and understanding how the organizational processes, procedures and skills needed to collect and analyze big data are the "bricks" in building this new structure.

6. Limitations and Suggestions for Future Research

Despite the contributions our study makes to the literature, it still has several limitations. First, as in most survey-method based papers, the reports about the firm's performance were self-reports and inferred from the managers' personal responses (e.g. Santoro, Bresciani & Papa, 2018). In addition, we used data only from managers in the EU. Therefore, it is difficult to generalize our findings to other settings.

However, these limitations also create the opportunity for future studies. First, we believe there is still a need to explore the antecedents of organizational BDA capabilities. Other factors may matter in the relationship between BDA, ambidexterity, agility and performance. Second, it would be interesting to investigate the phenomenon using qualitative methods such as multiple case studies. Finally, we could test the same model using a sample of managers of small and medium-size companies to determine whether the factors and effects are similar to or different from those in larger organizations.

References

Akter, S., Wamba, S.F., Gunasekaran, A., Dubey, R., & Childe, S.J. (2016). How to improve firm performance using big data analytics capability and business strategy alignment?. *International Journal of Production Economics*, *182*, 113-131.

Arbuckle, J. (2013). *AMOS 22. User's Guide. Chicago*. Chicago, IL: SmallWaters Corporation.

Armstrong, J.S., & Overton, T.S. (1977). Estimating nonresponse bias in mail surveys. *Journal of Marketing Research*, *14*(3), 396-402.

Bagozzi, R.P., & Yi, Y. (1988). On the evaluation of structural equation models. *Journal of the Academy of Marketing Science*, *16*(1), 74-94.

Baruch, Y. (1999). Response rate in academic studies—A comparative analysis. *Human Relations*, *52*(4), 421-438.

Bentler, P.M. (1990). Comparative fit indexes in structural models. *Psychological Bulletin*, *107*(2), 238-252.

Bloch, M., Blumberg, S. & Laartz, J. (2012). Delivering large-scale IT projects on time, on budget, and on value. McKinsey & Company Insights & Publications, October 2012.

Braganza, A., Brooks, L., Nepelski, D., Ali, M. & Moro, R. (2017). Resource management in big data initiatives: Processes and dynamic capabilities. *Journal of Business Research*, *70*, 328-337.

Bresciani, S., Ferraris, A., & Del Giudice, M. (2018). The management of organizational ambidexterity through alliances in a new context of analysis: Internet of Things (IoT) smart city projects. *Technological Forecasting and Social Change*, *136*, 331-338.

Cappellesso, G., & Thomé, K. M. (2019). Technological innovation in food supply chains: systematic literature review. *British Food Journal*, *121*(10), 2413-2428

Caputo, A., Marzi, G., & Pellegrini, M.M. (2016). The internet of things in manufacturing innovation processes: development and application of a conceptual framework. *Business Process Management Journal*, *22*(2), 383-402.

Cegarra-Navarro, J.G., Soto-Acosta, P., & Wensley, A.K. (2016). Structured knowledge processes and firm performance: The role of organizational agility. *Journal of Business Research*, *69*, 1544-1549.

Chen, H., Chiang, R.H., & Storey, V.C. (2012). Business intelligence and analytics: from big data to big impact. *MIS Quarterly*, *36*(4), 1165-1188.

Chiang, W.Y. (2018). Applying data mining for online CRM marketing strategy: An empirical case of coffee shop industry in Taiwan. *British Food Journal*, *120*(3), 665-675.

Cillo, V., Rialti, R., Del Giudice, M., Usai, A. (2019). Niche tourism destinations' online reputation management and competitiveness in big data era: evidence from three Italian cases. *Current Issues in Tourism*. DOI: https://doi.org/10.1080/13683500.2019.1608918.

Cohen, J., Dolan, B., Dunlap, M., Hellerstein, J. M., & Welton, C. (2009). MAD skills: new analysis practices for big data. *Proceedings of the VLDB Endowment*, *2*(2),1481-1492.

Davenport, T.H., Barth, P., Bean, R. (2012). How 'big data' is different. *MIT Sloan Management Review*, *54*, 43–46.

De Mauro, A., Greco, M., Grimaldi, M., & Ritala, P. (2018). Human resources for Big Data professions: A systematic classification of job roles and required skill sets. *Information Processing & Management*, *54*(5), 807-817.

Dubey, R., Gunasekaran, A., Childe, S. J., Papadopoulos, T., Luo, Z., Wamba, S. F., & Roubaud, D. (2017). Can big data and predictive analytics improve social and environmental sustainability? *Technological Forecasting and Social Change*, *144*, 534-545.

Eisenhardt, K.M., & Martin, J.A. (2000). Dynamic capabilities: what are they? *Strategic Management Journal*, *21*(10-11), 1105-1121.

Erevelles, S., Fukawa, N., & Swayne, L. (2016). Big Data consumer analytics and the transformation of marketing. *Journal of Business Research*, *69*, 897-904.

Faraoni, M., Rialti, R., Zollo, L., & Pellicelli, A.C. (2019). Exploring e-Loyalty Antecedents in B2C e-Commerce: Empirical results from Italian grocery retailers. *British Food Journal*, *121*(2), 574-589.

Ferraris, A., Mazzoleni, A., Devalle, A., & Couturier, J. (2018). Big data analytics capabilities and knowledge management: impact on firm performance. *Management Decision*, *58*(8), 1923-1936.

Field, A. (2013). *Discovering statistics using IBM SPSS statistics*. SAGE, London.

Franke, G.R. (2010). Multicollinearity. *Wiley International Encyclopedia of Marketing*, John Wiley and Sons.

Gibson, C.B., & Birkinshaw, J. (2004). The antecedents, consequences, and mediating role of organizational ambidexterity. *Academy of Management Journal*, *47*(2), 209-226.

Gölgeci, I., Ferraris, A., Arslan, A., & Tarba, S. Y. (2019). European MNE subsidiaries' embeddedness and innovation performance: Moderating role of external search depth and breadth. *Journal of Business Research*, *102*, 97-108.

Grefen, P., Rinderle-Ma, S., Dustdar, S., Fdhila, W., Mending, J., & Schulte, S. (2018). Charting Process-Based Collaboration Support in Agile Business Networks: Aligning the Need for a Dynamic Internet of Processes from Industry and Research Perspectives. *IEEE Internet Computing*, *22*(3), 48-57.

Gunasekaran, A., Yusuf, Y.Y., Adeleye, E.O., Papadopoulos, T. (2018). Agile manufacturing practices: the role of big data and business analytics with multiple case studies. *International Journal of Production Research*, *56*(1-2), 385-397.

Gupta, M., George, J.F. (2016). Toward the development of a big data analytics capability. *Information & Management*, *53*(8), 1049-1064.

Gupta S., & Giri V. (2018). Ensure High Availability of Data Lake. In Gupta, S. and V. Giri, *Practical Enterprise Data Lake Insights* (pp. 261-295), Berkeley (CA): Apress.

Hashem, I.A.T., Yaqoob, I., Anuar, N.B., Mokhtar, S., Gani, A., & Khan, S.U. (2015). The rise of "big data" on cloud computing: Review and open research issues. *Information Systems*, *47*, 98-115.

Hayes, A.F. (2013). *Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach*. Guilford Press, New York, NY.

Henderson, J.C., & Venkatraman, N. (1993). Strategic alignment: leveraging information technology for transforming organizations. *IBM Systems Journal*, *32*(1), 4-16.

Hofacker, C.F., Malthouse, E.C., & Sultan, F. (2016). Big data and consumer behavior: Imminent opportunities. *Journal of Consumer Marketing*, *33*(2), 89-97.

Hong, K.K., & Kim, Y.G. (2002). The critical success factors for ERP implementation: an organizational fit perspective. *Information & Management*, *40*(1), 25-40.

Iivari, J. (1992). The organizational fit of information systems. *Journal of Information Systems*, *2*, 3-29.

Jansen, J.J., Tempelaar, M.P., Van den Bosch, F.A., & Volberda, H.W. (2009). Structural differentiation and ambidexterity: The mediating role of integration mechanisms. *Organization Science*, *20*(4), 797-811.

Johnson, J.S., Friend, S.B., & Lee, H.S. (2017). Big data facilitation, utilization, and monetization: Exploring the 3Vs in a new product development process. *Journal of Product Innovation Management*, *34*(5), 640-658.

Kanellis, P., Lycett, L., & Paul, R.J. (1999). Evaluating business information systems fit: from concept to practical application. *European Journal of Information Systems*, *8*, 65-76.

Khan, Z., & Vorley, T. (2017). Big data text analytics: an enabler of knowledge management. *Journal of Knowledge Management*, *21*(1), 18-34.

Kwon, O., Lee, N., & Shin, B. (2014). Data quality management, data usage experience and acquisition intention of big data analytics. *International Journal of Information Management*, *34*(3), 387-394.

Labrinidis, A., & Jagadish, H.V., 2012. Challenges and opportunities with big data. *Proceedings of the VLDB Endowment*, *5*(12), 2032-2033.

Laudano, M.C., Zollo, L., Ciappei, C., & Zampi, V. (2018). Entrepreneurial universities and women entrepreneurship: a cross-cultural study. *Management Decision*. DOI: 10.1108/MD-04-2018-0391.

LaValle, S., Lesser, E., Shockley, R., Hopkins, M.S., & Kruschwitz, N. (2011). Big data, analytics and the path from insights to value. *MIT Sloan Management Review*, *52*(2), 21-44.

Lee, O.K., Sambamurthy, V., Lim, K.H., Wei, & K.K. (2015). How does IT ambidexterity impact organizational agility?. *Information Systems Research*, *26*(2), 398-417.

Lu, Y., & Ramamurthy, K. (2011). Understanding the link between information technology capability and organizational agility: An empirical examination. *MIS Quarterly*, *35*(4), 931-954.

Manyika, J., Chui, M., Brown, B., Bughin, J., Dobbs, R., Roxburgh, C., & Byers, A.H. (2011). Big data: The next frontier for innovation, competition, and productivity. *McKinsey Global Institute* (http://www.mckinsey.com/insights/mgi/research/technology_and_innovation/big_data_the_next_frontier_for_innovation; accessed August 4, 2018.

McAfee, A. & Brynjolfsson, E. (2012). Big data: the management revolution. *Harvard Business Review*, *90*(10), 60-68.

Melville, N., Kraemer, K., & Gurbaxani, V. (2004.) Information technology and organizational performance: An integrative model of IT business value. *MIS Quarterly*, *28*(2), 283-322.

Mikalef, P,. & Pateli, A. (2017). Information technology-enabled dynamic capabilities and their indirect effect on competitive performance: Findings from PLS-SEM and fsQCA. *Journal of Business Research*, *70*, 1-16.

Nunnally, J.C., 1978. *Psychometric Theory*. New York, NY: McGraw Hill.

O'Reilly III, C.A., & Tushman, M.L. (2008). Ambidexterity as a dynamic capability: Resolving the innovator's dilemma. *Research in Organizational Behavior*, *28*, 185-206.

Pandey, S.C., & Dutta, A. (2013). Role of knowledge infrastructure capabilities in knowledge management. *Journal of Knowledge management*, *17*(3), 435-453.

Pauleen, D.J., & Wang, W.Y. (2017). Does big data mean big knowledge? KM perspectives on big data and analytics. *Journal of Knowledge Management*, *21*(1), 1-6.

Picón, A., Castro, I., & Roldán, J. L. (2014). The relationship between satisfaction and loyalty: A mediator analysis. *Journal of Business Research*, *67*, 746-751.

Podsakoff, P.M., MacKenzie, S.B., Lee, J.Y., & Podsakoff, N.P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*(5), 879-898.

Preacher, K.J., & Hayes, A.F. (2004.) SPSS and SAS procedures for estimating indirect effects in simple mediation models. *Behavior Research Methods, Instruments, & Computers*, *36*(4), 717-731.

Prescott, M., (2014(. Big data and competitive advantage at Nielsen. *Management Decision*, *52*(3), 573-601.

Provost, F., & Fawcett, T. (2013). Data science and its relationship to big data and data-driven decision making, *Big Data*, *1*(1), 51-59.

Rafferty, A.E., & Jimmieson, N.L. (2017). Subjective perceptions of organizational change and employee resistance to change: Direct and mediated relationships with employee well-being. *British Journal of Management*, *28*(2), 248-264.

Raguseo, E., & Vitari, C. (2018). Investments in big data analytics and firm performance: an empirical investigation of direct and mediating effects. *International Journal of Production Research*, *56*(15), 5206-5221.

Raisch, S., & Birkinshaw, J. (2008). Organizational ambidexterity: Antecedents, outcomes, and moderators, *Journal of Management*, *34*(3), 375-409.

Rialti, R., Zollo, L., Pellegrini, M.M., & Ciappei, C. (2017). Exploring the antecedents of brand loyalty and electronic word of mouth in social-media-based brand communities: do gender differences matter?. *Journal of Global Marketing*, *30*(3), 147-160.

Rialti, R., Marzi, G., Silic, M., & Ciappei, C. (2018). Ambidextrous organization and agility in big data era: the role of business process management systems. *Business Process Management Journal*, 24 (5), 1091-1109.

Rialti, R., Marzi, G., Ciappei, C., & Busso, D. (2019). Big data and dynamic capabilities: a bibliometric analysis and systematic literature review. *Management Decision*, *57*(8), 2052-2068.

Roßmann, B., Canzaniello, A., von der Gracht, H., & Hartmann, E. (2018). The future and social impact of Big Data Analytics in Supply Chain Management: Results from a Delphi study. *Technological Forecasting and Social Change*, *130*, 135-149.

Santoro, G., Fiano, F., Bertoldi, B., & Ciampi, F. (2018). Big data for business management in the retail industry. *Management Decision*, *58*(8), 1980-1992.

Santoro, G., Bresciani, S., & Papa, A. (2018). Collaborative modes with cultural and creative industries and innovation performance: the moderating role of heterogeneous sources of knowledge and absorptive capacity. *Technovation*, DOI: https://doi.org/10.1016/j.technovation.2018.06.003

Scuotto, V., Ferraris, A., & Bresciani, S. (2016). Internet of Things: Applications and challenges in smart cities: a case study of IBM smart city projects. *Business Process Management Journal*, *22*(2), 357-367.

Soto-Acosta, P., & Cegarra-Navarro, J.G. (2016). New ICTs for knowledge management in organizations. *Journal of Knowledge Management*, *20*(3), 417-422.

Soto-Acosta, P., Popa, S., & Martinez-Conesa, I. (2018). Information technology, knowledge management and environmental dynamism as drivers of innovation ambidexterity: a study in SMEs. *Journal of Knowledge Management*, *22*(4), 824-849.

Tallon, P.P., & Pinsonneault, A. (2011). Competing perspectives on the link between strategic information technology alignment and organizational agility: insights from a mediation model. *MIS Quarterly*, *35*(2), 463-486.

Tan, K. H., Zhan, Y., Ji, G., Ye, F., & Chang, C. (2015). Harvesting big data to enhance supply chain innovation capabilities: An analytic infrastructure based on deduction graph. *International Journal of Production Economics*, *165*, 223-233.

Tarafdar, M., & Qrunfleh, S. (2017). Agile supply chain strategy and supply chain performance: complementary roles of supply chain practices and information systems capability for agility. *International Journal of Production Research*, *55*(4), 925-938.

Teece, D., Peteraf, M., & Leih, S. (2016). Dynamic capabilities and organizational agility: Risk, uncertainty, and strategy in the innovation economy. *California Management Review*, *58*(4), 13-35.

Teece, D.J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, *18*(7), 509-533.

Waller, M.A., & Fawcett, S.E. (2013). Data science, predictive analytics, and big data: a revolution that will transform supply chain design and management. *Journal of Business Logistics*, *34*(2), 77-84.

Wamba, S.F., Gunasekaran, A., Akter, S., Ren, S.J.F., Dubey, R., & Childe, S.J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. *Journal of Business Research*, *70*, 356-365.

Wamba, S.F., & Mishra, D. (2017). Big data integration with business processes: a literature review. *Business Process Management Journal*, *23*(3), 477-492.

Wang, G., Gunasekaran, A., Ngai, E.W., & Papadopoulos, T. (2016). Big data analytics in logistics and supply chain management: Certain investigations for research and applications. *International Journal of Production Economics*, *176*, 98-110.

Wang, Y., Kung, L., & Byrd, T.A. (2018). Big data analytics: Understanding its capabilities and potential benefits for healthcare organizations. *Technological Forecasting and Social Change*, *126*, 3-13.

Weber, Y., & Tarba, S.Y. (2014). Strategic Agility: A State of the Art Introduction to the Special Section on Strategic Agility. *California Management Review*, *56*(3), 5-12.

Yi, X., Liu, F., Liu, J., & Jin, H., (2014). Building a network highway for big data: architecture and challenges. *IEEE Network*, *28*(4), 5-13.

Zollo, L., Faldetta, G., Pellegrini, M.M., & Ciappei, C. (2017). Reciprocity and gift-giving logic in NPOs. *Journal of Managerial Psychology*, *32*(7), 513-526.

Zollo, L., Laudano, M.C., Boccardi, A., & Ciappei, C. (2019). From governance to organizational effectiveness: the role of organizational identity and volunteers' commitment. *Journal of Management and Governance*, *23*(1), 111-137.

Zollo, L., Yoon, S., Rialti, R., & Ciappei, C. (2018). Ethical consumption and consumers' decision making: the role of moral intuition. *Management Decision*, *56*(3), 692-710.

Big Data Analytics Capabilities and Performance:

Evidences from a moderated multi-mediation model

Authors:

Dr. Riccardo Rialti

University of Florence, Department of Economics and Management,

E-mail: riccardo.rialti@unifi.it

Lamberto Zollo

University of Florence, Department of Economics and Management,

Email: lamberto.zollo@unifi.it

Dr. Alberto Ferraris

Department of Management – University of Torino

E-mail: alberto.ferraris@unito.it

and

Research Fellow of the Laboratory for International and Regional Economics,

Graduate School of Economics and Management,

Ural Federal University, Russia.

Prof. Ilan Alon

Department of Management, University of Adger,

Email: ilan.alon@uia.no

Riccardo Rialti collaborates with the University of Florence (Italy). He got a PhD in Business Administration and Management from the University of Pisa in 2019. He has been a visiting researcher at University of Lincoln (UK), Middlesex University London (UK), Sophia University (JP), ESCP Europe (FR). His main research interests are related with the impact of big data and big data analytics on businesses' management. In detail, over the years his research focused on big data, organizational dynamic capabilities, knowledge management and ambidexterity. His papers have been published both on national and international journal such as MD, BPMJ, CIT, BFJ, JGM, and WREMSD. Over the last year Riccardo also started to work as a strategic consultant for SMEs wishing to digitalize and to expand their business.

Lamberto Zollo is an Assistant Professor in Management at the University of Florence, Italy. He holds a PhD in Business Administration and Management (University of Pisa, Italy) and a Master in Big Data for Management (University of Florence, Italy). He is Editorial Advisory Board member of Management Decision and Editorial Review Board member of Journal of Global Fashion Marketing. His research interests are in business ethics, ethical consumption, and strategic management. His research has been published in international journals such as Journal of Business Ethics, Journal of Managerial Psychology, and Management Decision.

Alberto Ferraris received his PhD in Business and Management at the Department of Management, University of Turin (Italy) in 2015. He is currently working as a Senior Researcher at the University of Turin - Department of Management. He obtained the qualification of Associate Professor at the National Scientific Evaluation (ASN) in Italy in 2017. He is also Research Fellow of the Laboratory for International and Regional Economics, Graduate School of Economics and Management, Ural Federal University (Russia). He is Fellow (F-EMAB) of the EuroMed Research Business Institute (www.emrbi.com) and he is author of several academic and scientific articles published on international journal such as Technological Forecasting and Social Change, R&D Management, Journal of Business Research and Journal of Knowledge Management. In 2014, he won the Best Student Paper Award, "A new actor in the development of Social Innovation" at the 7th EuroMed Conference in Kristiansand (Norway) and one year later he was awarded with the "2015 Emerald/EMRBI Business Research Award for Emerging Researchers" with the paper: "International diversification and firm performance: A four stage model".

Ilan Alon is Professor of Strategy and International Marketing at the School of Business and Law at the University of Agder. He holds a Ph.D. from Kent State University (USA). His publications

have appeared in journals, such as *Harvard Business Review, Management International Review, International Business Review, Journal of International Marketing,* and *International Marketing Review*. His books are published by Palgrave, Routledge, McGraw-Hill and others.
Alon is the Head of International Affairs for the School of Business and Law at the University of Agder, and former leader of the Emerging Markets research group. He is also Editor-in-Chief of the *International Journal of Emerging Markets* and the *European Journal of International Management*.