# Big data analytics business value and firm performance: Linking with environmental context

Claudio Vitari, Elisabetta Raguseo

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**Authors: Claudio Vitari, Elisabetta Raguseo**

## Abstract

Previous studies, grounded on the resource based view, have already explored the relationship between the business value that Big Data Analytics (BDA) can bring to firm performance. However, the role played by the environmental characteristics in which companies operate has not been investigated in the literature. We inform the theory, in that direction, via the integration of the contingency theory to the resource based view theory of the firm. This original and integrative model examines the moderating influence of environmental features on the relationship between BDA business value and firm performance. The combination of survey data and secondary financial data on a representative sample of medium and large companies makes possible the statistical validation of our research model. The results offer evidence that BDA business value leads to higher firm performance, namely financial performance, market performance and customer satisfaction. More original is the demonstration that this relationship is stronger in munificent environments, while the dynamism of the environment does not have any moderating effect on the performance of BDA solutions. It means that managers working for firms in markets with a growing demand are in the best position to profit from BDA.

## Keywords

Resource based view, contingency theory, Big Data Analytics, customer satisfaction, financial performance, market performance, munificence, dynamism.

## 1 Introduction

Organisations are increasingly interested in the potential of big data and an increasing proportion of private and public organisations (Amankwah-Amoah, 2016) create and adopt solutions to exploit this asset (McAfee et al., 2012). Big Data is considered here as "*the information asset characterized by such a high volume, velocity and variety to require specific technology and analytical methods for its transformation into Value*" (De Mauro et al., 2016). As far as big data is an asset, the Resource Based View (RBV) gives a framework to the organizations for their investments in it to create value. However, big data solutions can be very diverse and they can affect value in different ways (Ardito et al., 2018). Production domain is exemplar in this diversity, as it is at the forefront to exploit big data (Tan et al., 2017; Zhou et al., 2019). Indeed, manufacturing is an intensive user of big data and stores more data than any other sector, such as: to discover new patterns, perform simulations, pilot industry 4.0 (Zhou et al., 2019), manage complex systems in real-time (van der Spoel et al., 2017), enhance production yields (Baily and Manyika, 2013; A. Kumar et al., 2016), and transform supply chains (Baryannis et al., 2019; Gunasekaran et al., 2017; Hofmann, 2017; Ivanov et al., 2019; Pan et al., 2017; G. Wang et al., 2016).

But not all the production activities play on the same plain big data field. Some suggest that the environmental context may have a significant role in it and contingency theory would justify it (Dale Stoel and Muhanna, 2009; Mariani et al., 2019; Pratono, 2016). However, research has not fully considered the effects of environmental context on the relationship between various big data solutions and performance.

This exploration becomes relevant if we consider that prospectively, the worldwide revenues of big data and business analytics are expected to "grow from nearly $122 billion in 2015 to more than $187 billion in 2019, an increase of more than 50% over the five-year forecast period" (IDC, 2016). Big data attracts investments because it promises to create added value in a variety of operations (OECD, 2013) and it has been identified as the "next big thing" in innovation (Gobble, 2013; Wamba et al., 2017a). Big data benefits and risks are recognized by the firms adopting them (Del Vecchio et al., 2018). However, the literature shows that several Information Technologies (IT) had been announced as creating value but, once implemented in the organisations, did not actually satisfy the expectations. This bandwagon phenomenon has not yet been eradicated, even if several researchers have regularly raised alerts on this risk, for example around e-business (Coltman et al., 2000), green Information Systems (IS) (Dedrick, 2010) and blockchain (Avital et al., 2016). Today, big data is highly debated and publicly promoted by policy makers and the mass media. This prominence could swamp organisations' deliberative behaviours (Swanson and Ramiller, 2004), as happened in previous bandwagon cycles. Hence, the complex and crucial question of "*Whether, when, and how to innovate with IT,* confronts managers in virtually all of today's enterprises" (Swanson and Ramiller, 2004, p. 553) and could also be raised for big data initiatives. Is big data the current "me too" phenomenon?

Alerts have recently been launched to inform managers that big data is not a panacea (Akter et al., 2016; Jones, 2019), such as the axiom that "an uncritical analysis of poorly understood data sets does not generate knowledge" (Matthias et al., 2017, p. 41). Multiple dangers exist like the mismanagement of inconsistent and unreliable data (Lukoianova and Rubin, 2014), the failure of management to develop new perspective and innovative capabilities (Akter et al., 2016), or the inability to let data talk through "interesting and insightful questions" (Matthias et al., 2017, p. 49). Many companies have been overrun by a data-driven revolution in management (Tambe, 2014).

Hence, research is needed to face the enormous challenge of knowing how big data can be used to support decision-making (Bi et al., 2019a, 2019b; Li et al., 2016; Matthias et al., 2017; Tan et al., 2017), finding a positive Return On Investment on the large investments required in this domain, which could otherwise jeopardise the entire organisation (Braganza et al., 2017).

On one hand, a research direction that is still relatively unexplored for big data, but potentially meaningful (Côrte-Real et al., 2017), concerns the understanding of the environmental variables on business value of big data solutions and firm performance. Industry-related environmental effects are regularly recognized as possible important factors playing a moderating role on firm performances when considering the impact of IT (Dale Stoel and Muhanna, 2009; Li and Ye, 1999). Hence, the right combination of endogenous mechanisms with external variables could help firms achieve a competitive advantage (Burns and Stalker, 1994; Thompson et al., 1992).

On the other hand, among the various big data studies recently focused on production needs (Tan et al., 2017) scant attention, relative to its importance for big data, has been paid to Big Data Analytics (BDA) solutions. BDA solutions have been defined as "*a holistic approach to managing, processing and analysing the 5V data-related dimensions (i.e. volume, variety, velocity, veracity and value) to create actionable insights in order to deliver sustained value, measure performance and establish competitive advantages*" (Wamba et al., 2015, p. 6). This definition provides a holistic approach to the three complementary dimensions in BDA: management, technology and human (Akter et al., 2016). This approach has been successfully applied in the production domain, as such, to make lean six sigma projects more effective (Gupta et al., 2019), to forecast cycle time (Wang and Zhang, 2016), to manage the logistics at the manufacturing shop floors (Zhong et al., 2017), and at the metropolitan level (Yang et al., 2019), and shipping in retail 4.0 (M. Kumar et al., 2016; Lee, 2017). Practitioners and academics have raised the need to continue research on BDA solutions in order to understand how, when and why BDA can be a valuable resource for organisations to gain competitive advantages (Abbasi et al., 2016; Agarwal and Dhar, 2014; Côrte-Real et al., 2017;

Erevelles et al., 2016; LaValle et al., 2011; Xu et al., 2016). This is specifically true for production research, as far as the BDA can be helpful to support global manufacturing and supply chain innovation by creating data transparency, improving human decision-making and promoting innovative business models (Manyika et al., 2011; Tan et al., 2017).

Based on these considerations, our original contribution is centred on the inclusion of the environmental variables, such as environmental dynamism and environmental munificence, in the understanding of the impact of BDA on firm performance. The aim of this study was thus to address the following research question: *To what extent do environmental dynamism and environmental munificence moderate the effect of the business value of BDA solutions on the performance of a firm?* The combination of survey data and secondary financial data on a representative sample of medium and large companies will allows to answering our research question.

The rest of the paper is structured as follows. First, we present the theoretical background from a RBV perspective, and formulate our hypotheses. We then detail the methodology that we followed and present our results. We continue with a discussion of the findings, our conclusions and guidelines for future studies.

## 2 Theoretical foundations and research hypotheses

Interest in assessing business value and firm performance of BDA solutions is increasing (Akter et al., 2016; Kamble and Gunasekaran, 2019; Kiron et al., 2014; McAfee et al., 2012). Initial results put forward that these analytics solutions could be the critical elements that are needed to transform overwhelming data into business value and ultimately into business performance. "*BDA is now considered a game changer that can enable improved business efficiency and effectiveness because of its high operational and strategic potential*" (Wamba et al., 2017a). Several studies have highlighted the effects of BDA business value on firm performance (Ji-fan Ren et al., 2016; Raguseo and Vitari, 2018). At the same time, practitioners and academics have raised the need to continue research in order to understand how, when and why BDA can be a valuable resource for organisations to gain competitive advantages (Abbasi et al., 2016; Agarwal and Dhar, 2014; Côrte-Real et al., 2017b; Erevelles et al., 2016; LaValle et al., 2011; Xu et al., 2016). The integration of the resource based view theory of the firm with the contingency theory aims to this understanding.

### *2.1 Resource based view*

The RBV theory of the firm can explain the extent to which BDA solutions contribute to the creation of a competitive edge (Wamba et al., 2017a). A firm obtains a competitive edge when it enjoys greater success than its competitors (Davenport, 2006; Peteraf and Barney, 2003). In the RBV, it is important to distinguish business value from firm performance (Ji-fan Ren et al., 2016). Business value is the central construct of the RBV and it stands between the rare, inimitable and non-substitutable resources of the firm and the performance of the firm (Kozlenkova et al., 2014; Melville et al., 2004).

In line with this stream of research grounded on the RBV, we propose that BDA solutions could generate, firstly, a higher business value, and, subsequently, a higher firm performance. The emergence of the business value dimension for big data is relatively recent in time. At the beginning, big data was characterised by three Vs: "high-Volume, high-Velocity and/or high-Variety" (Gartner, 2012). The fourth V, Veracity (Lukoianova and Rubin, 2014), and fifth V, Value (Wamba et al., 2015), were theorized later on. Including the five V dimensions of big data in the RBV means that big data are a rare, inimitable and non-substitutable information asset characterized by their high Volume, high Velocity, high Variety, and uncertain Veracity. The business Value extracted from this asset completes the four other Vs of big data as information asset. Unfortunately, extracting business value from this information asset is the most critical problem due to the intrinsic complexity of data characterized by high Volume, high Velocity, high Variety, and uncertain Veracity (Chen et al., 2014).

### *2.2 Effect of the business value of BDA solutions on firm performance*

The effect of the business value of BDA solutions on firm performance depends on the specific big data solutions that the organisations set up, in relation to their scale, their time horizon (Matthias et al., 2017) and nature (G. Wang et al., 2016; Wang et al., 2018). Concerning their scale, a big data application can have a narrow scale, covering a single operation of a business process, such as product suggestions, while another application can have a wider scope, covering entire business domains, such as a whole supply chain (G. Wang et al., 2016). Concerning their time horizon and nature, a big data application can have a past, hence descriptive, orientation, such as in auditing solutions. Otherwise a big data application can have a present and predictive orientation (Lee, 2017; Priya and Ranjith Kumar, 2015; van der Spoel et al., 2017), such as real-time trading tools. Finally, a big data application can have a future, hence prescriptive (Amankwah-Amoah, 2016), orientation for example in strategic decision-support systems (Bi et al., 2019a, 2019b; Gunasekaran et al., 2017). The various possible combinations explain why BDA solutions could potentially provide business value in the most diverse activities of any organisation (Tan et al., 2015; Wamba et al., 2015; Wang et al., 2018).

Given this diversity in the applicability of big data, we look at firm performance, by taking into consideration the financial performance, the market performance and the customer satisfaction.

Two studies (Ji-fan Ren et al., 2016; Raguseo and Vitari, 2018) have already looked at the relationship between the business value of BDA solutions and firm performance, employing to different extent these three dimensions of firm performance. The first (Ji-fan Ren et al., 2016) considered firm performance as composed of two dimensions: financial and market performance. Financial performance referred to revenue growth and profitability, while market performance was about improving a firm's position against its competitors (Mithas et al., 2011; Tippins and Sohi, 2003). The second (Raguseo and Vitari, 2018) added customer satisfaction into the equation and justified that customer satisfaction and market performance are mediating variables between the business value of BDA solutions and financial performance. The results of these studies suggested that the business value of BDA solutions has an impact on the performance of a firm, with no mediating effects, when firm performance is measured as composed of financial and market performance (Ji-fan Ren et al., 2016), and with customer satisfaction and market performance as mediating variables when exclusively financial performance is the dependent variable (Raguseo and Vitari, 2018). As a consequence, our dependent variable, firm performance, includes these three dimensions: financial performance, market performance and customer satisfaction, defined as followed.

The financial performance of a firm is a commonly examined dependent variable measuring the competitive advantage of a company (Kaufman, 2015). Initial evidence emerging from the literature attest of the opportunities, through BDA solutions, to greatly improve financial performance (Akter et al., 2016; Wamba et al., 2015, 2017a). Results show that BDA solutions can improve Return On Investment for retailers (Wamba et al., 2017a), procurement processes (Bock and Isik, 2015), or e-commerce purchasing process completion (Jayanand et al., 2014).

Market performance refers to the organisation's ability to have higher market shares, to enter new markets more rapidly, to introduce new products and services more frequently, and to have higher product and service success rates, than its competitors. Scholars have already advanced that big data can be incorporated in marketing and new product development (Tan et al., 2015; Wamba et al., 2015, 2017a; Xu et al., 2016). BDA solutions would facilitate the recognition of market opportunities and threads and define the best market, product and service strategies through a data lens (Brands, 2014; Côrte-Real et al., 2017; Davenport, 2014), via for example a better customer segmentation (Wamba et al., 2015). BDA solutions could also open to new kinds of commercial offers that leverage the digitalisation processes, being potentially disruptive of the traditional business models and generating new revenue streams by selling information complementarily to the traditional product and service offers (Opresnik and Taisch, 2015).

Customer satisfaction is a function of how goods and services meet or surpass the expectations of customers. In general, a customer compares the perceived performance of a product with her performance standard. The customer is satisfied when her perceived performance is greater than her performance standard, and dissatisfied when her performance falls short. BDA solutions could improve how customers understand and exploit this better knowledge to increase customer satisfaction (Wamba et al., 2017b), decrease customer acquisition costs (Liu, 2014), strengthen the customer relationship (Cheng et al., 2016), improve customization (Wamba et al., 2015), and improve overall customer experience (Tan et al., 2015; Tweney, 2013).

### *2.3 Contingency theory*

The role played by the environmental context, in the relationship between BDA value and firm performance, has not yet been investigated. To understand this aspect, we propose to lever the contingency theory and to integrate this theory to the RBV perspective.

The contingency theory advances that organizational effectiveness results from fitting the characteristics of the organisation to the contingencies that reflect the situation of the organisation (Dale Stoel and Muhanna, 2009; Donaldson, 2001): the better the fit, the higher the organisational performance. Hence, contingency theory has the intention to understand how firms align their expected performance with both the internal and external business environment (Homburg et al., 2012). Moreover, the attaining of the fit is a continuous seek due to the changing contingencies over time.

The external environment is one of the first and most important identified contingencies (Burns and Stalker, 1961), followed by strategy and organizational size (Child, 1975). Hence, organizations should not only acquire and develop their resources, as advanced by the RBV (Barney, 1991), but they also should enhance the capability to deal with environmental contingencies. The right combination of endogenous mechanisms with external variables could help firms achieving a competitive advantage (Burns and Stalker, 1994; Thompson et al., 1992).

In line with the contingency theory development, we propose that the environmental variables could influence the organisational alignment, moderating the relationship of the BDA value on firm performance. A moderator is a variable that affects the direction and/or strength of the relationship between an independent and a dependent variable (Baron and Kenny, 1986). Even though, big data are rare, inimitable and non-substitutable information assets, extracting business value from this information asset would be moderated by the environmental contingencies. Industry-related environmental effects are regularly recognized as possible important factors playing a moderating role on firm performances when considering the impact of Information Technology (IT) (Li and Ye, 1999).

More specifically, we consider the levels of munificence and dynamism in the environment where firms do business. These moderators are used extensively in Information Systems (IS) studies (e.g., Venkatesh et al., 2012), as the external challenges that firms have to face.

### *2.4 Moderating effect of the environmental dynamism*

Environmental dynamism appears to constitute a critical dimension of a firm's exogenous environment. Environmental dynamism refers to the rate of instability in an industry, which could concern changes in customer preferences and/or competitor strategies (Dale Stoel and Muhanna, 2009). The contingency theory recognizes that Environmental dynamism can have the power to moderate business performance (Lumpkin and Dess, 2001; Teece et al., 1997) and it constitutes a central factor explaining the degree of success in the development of organisational resources (Simerly and Li, 2000; Wu, 2010). In practice, contingency theory contributes to the explanation of the accentuated managerial risks existing in industries that are highly dynamic. The managers experience much more uncertainty and have only little pieces of doubtful information. Moreover, possible developments and strategic options are not clearly visible to the firm. These risks and this lack of visibility can potential impact the firm ability to convert value into performance (Rösmann et al., 2017).

The contingency theory highlight that, in these dynamic environments, response time is particularly important (Bechor et al., 2010). In this context, investments in IT may serve as an effective way to provide timely and relevant information to upper managers and thus to reduce levels of uncertainty (Li and Richard Ye, 1999). When firms are slow to respond, they may miss opportunities or be pre-empted by competitors (Bhatt et al., 2010). Conversely, firms that respond quickly to customer changes or competitor moves may often realise long-term performance benefits.

Thanks to the integration of the RBV theory and the contingency theory, we expect that firms able to generate higher business value from their BDA solutions can achieve better firm performance in dynamic environments. For example, a present orientation in BDA solution could be leveraged based on real-time reactions, and accentuates the organizational agility (Côrte-Real et al., 2017; Wang et al., 2018). BDA solutions may provide organisations with insight into customers' expressed and latent needs, and the velocity dimension of the big data may be a key to transform these insights into better customer satisfaction, higher market performance and stronger financial results (Hofmann, 2017).

Based on these considerations, we expect that firms that develop high levels of BDA solutions achieve higher levels of firm performance under high levels of environmental dynamism. This grounds our first set of hypotheses:

*H1: The higher the level of environmental dynamism, the higher the contribution of BDA solutions will be to firm performance, in terms of (H1a) financial performance, (H1b) market performance, and (H1c) customer satisfaction.*

### *2.5 Moderating effect of environmental munificence*

The contingency theory advances that environmental munificence could be an equally important dimension that should be taken into account. Munificence refers to the extent to which opportunities exist and the degree to which an environment makes resources available to sustain growth (Dale Stoel and Muhanna, 2009; Rosenbusch et al., 2013). Munificent environments are characterised by growth in customer demands; thus, firms must be prompt in responding to growing customer needs (Xue et al., 2012). Environmental munificence also enhances the value of the organisational resources that promote low operating costs (Terjesen et al., 2011).

The contingency theory would support also that munificent environments could extend the potential of BDA solutions in experimentation and innovation (Tan et al., 2015; Wamba et al., 2015) and their transformation in firm performance. A future orientation of a firm's BDA solution (Gunasekaran et al., 2017) could generate higher benefits when a new forward looking strategic initiative matches with a contingent environment with a growing demand. The BDA solutions could facilitate, for example in the fashion industry, the suppliers to perceive where and when a specific style of clothing may become the top seller (Dale Stoel and Muhanna, 2009). Thus, the teachings of the contingency theory would support the proposition that the value adding potential of superior

BDA solutions is likely to be more pronounced in highly munificent environments. Finally, the analysis of big data may support more timely interactions with new opportunities (e.g., proposing new offers to customers). Such interactions may in turn reveal a variety of avenues for business expansion and profit. In short, the integration of the RBV theory and the contingency theory would raise expectations that firm performance resulting from BDA solutions would be more pronounced in highly munificent environments. This establishes the ground of our second set of hypotheses:

*H2: The higher the level of environmental munificence, the higher the contribution of BDA solutions will be to firm performance, in terms of (H2a) financial performance, (H2b) market performance, and (H2c) customer satisfaction.*

Overall, we test the research model shown in Figure 1 by drawing on RBV and contingency theory. We argue that the business value derived from the use of BDA solutions has an impact on the firm performance, through the contribution of two moderating variables: environmental munificence and environmental dynamism.

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**Figure 1. Research framework**

## 3 Methodology

A cross-sectional survey was used to collect the data and test the research model shown in Figure 1. Details are shown in the following paragraphs.

### *3.1 Data collection*

We administered our questionnaire to medium- and large-sized French firms to evaluate the impact of the BDA business value on the firm performance. As our study considers the effects at the firm level, we followed previous studies that targeted the Chief Information Officer (CIO) as the main informant.

We implemented a random sampling method to select medium and large French companies to interview from a population of 19,875 medium and large companies belonging to the sectors shown in Table 1 and registered in the Bureau Van Dijk's DIANE database, which is one of the main sources of financial information on firms in France. We aimed to gather 200 questionnaires, assuring a 95% confidence level and a 6.9% confidence interval in representing the whole starting population. Firms were categorized by size based on their revenues, accordingly to the European definition, where small companies generate less than 10€ million, medium-sized firms between 10€ and 50€ million, and large companies more than 50€ million.

We conducted a pilot study with 30 companies, contacting a sample of 142 companies (response rate of 21.13%), to test the comprehensibility of the questions, to identify possible response issues, to establish the expected response rate and hence the sampling needs. All the questions led to appropriate answers and thus did not require further changes. Therefore, the final questionnaire remained unchanged.

To attain our target of 200 valid questionnaires, we looked for 170 additional valid questionnaires, beyond the 30 valid questionnaires gathered for the pilot. Our search for 170 additional valid questionnaires brought us to contact a sample of 1,962 additional companies (response rate of 8.66%). The data gathering process involved three steps. In the first step, we contacted the company to inform them about the aim of the research study and to ask permission to contact the CIO. In the second step, the CIO was contacted and asked about his/her willingness to participate in the survey. When the CIO was not available at the time agreed upon in the first call, we made a second appointment. Therefore, the questionnaire was completed, either in the second or third step, according to the availability of the CIO. When the CIO was unable to answer the questionnaire, we identified another qualified respondent knowledgeable about the firm's investments and the adoption of BDA solutions.

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**Table 1. Sample characteristics**

### *3.2 Measures*

The questionnaire consisted of two sections. The first section, which all companies answered, assessed the presence or absence of BDA solutions. This first section included questions to triangulate the presence of big data in its three founding dimensions: Velocity, Variety and Volume. The following question was included for Velocity: *Up to now, what is the shortest latency of your data?* Respondents had a single choice possibility, among the following alternatives:

- Real-time (data is updated in the database as the event occurs, with little or no latency),
- Near-time (data is updated in the database at set and regular time intervals),
- After a long time (data is updated in the database only once, or irregularly)

The following question was included for Variety: *Up to now, what are the sources of data of your company, beyond traditional databases?* Respondents had a multiple choice possibility, among the following list of sources:

- Radio Frequency Identification system data
- Clickstream data
- Smart/intelligent/connected meters data or other smart/intelligent/connected object data
- Global Positioning System data
- Point Of Sales data or other transactional data sources
- Social media posts
- Weblogs posts
- Microblogs (eg. Tweets) posts
- Online portal content
- Email message content
- Other natural language text sources
- Audio sources
- Image sources
- Video sources
- Other sources_____Please specify

The following question was included for Volume: *Up to now, what is the total amount of data stored in all the database of your company?* Respondents had a single choice possibility, among the following alternatives:

- Less than 1 Terabyte,
- Between 1 Terabyte and 1 Petabyte,
- Between 1 Petabyte and 1 Exabyte,
- Between 1 Exabyte and 1 Zettabyte,
- More than 1 Zettabyte

In search for big data, we set a threshold for each question. As far as Velocity was concerned, we looked for real-time or near-real-time latency. The presence of more than one data source was assessed to establish Variety. As for Volume, we asked whether the size of the stored data exceeded a Petabyte. If, at least, one response passed its respective threshold, we deduced that the organisation could have a BDA solution. Hence we explicitly asked the respondents to confirm our deduction that the organisation has BDA solutions. Only if the respondent explicitly confirmed our deduction, the company was asked to fill in the second section of the questionnaire.

In the second section, we checked once again whether the company had at least one BDA solution, by asking about the kinds of BDA solutions the company had, among the following list, offering a multiple choice possibility:

1. Visual analytics software or other software used to display analytical results in visual formats.
2. Scripting languages or other programming languages that work well with big data (e.g., Python, Pig, and Hive).
3. In-memory analytics software or other processing big data used in computers for greater speed.
4. MapReduce and Hadoop software or other software used to process big data across multiple parallel servers.
5. Machine learning software or other software used to rapidly find the model that best fits a data set.
6. Natural language processing or other software used for texts - information extraction, text summarization, question answering, or sentiment analysis.
7. Social media analytics software (content-based analytics and structure-based analytics).
8. Predictive analytics software used to extract information from data and predict trends and behaviour patterns.

Beyond this double check question, the second section assessed the dependent and independent variables of our empirical model: firm performance and BDA business value (Table 2 and Figure 2).

### *3.2.1 Dependent variable*

*Firm performance*. It is defined as the financial performance, market performance and customer satisfaction of the organisation (Ji-fan Ren et al., 2016; Raguseo and Vitari, 2018). Financial performance refers to the firm's ability to improve profitability and return on investment. It was assessed using three items based on a seven-point Likert scale, with responses ranging from "completely disagree" (−3) to "completely agree" (+3) (Ji-fan Ren et al., 2016; Mithas et al., 2011). Market performance refers to the firm's ability to gain and retain customers. It was assessed using four items based on a seven-point Likert scale, with responses ranging from "completely disagree" (−3) to "completely agree" (+3) (Ji-fan Ren et al., 2016). Customer satisfaction refers to the firm's ability to meet or surpass customer expectations. It was assessed using four items based on a seven-point Likert scale, with responses ranging from "completely disagree" (−3) to "completely agree" (+3) (Mithas et al., 2011; Vorhies and Morgan, 2005).

### *3.2.2 Independent variable*

*BDA business value*. It is defined as the transactional, strategic, transformational and informational value of the BDA solution (Ji-fan Ren et al. 2016). It is the combination of four sub dimensions and it is operationalized as a second-order variable (Figure 2). The first, transactional value refers to the

degree to which the user perceives that BDA solutions provide operational benefits as reducing operating costs or communication costs. It was assessed using four items based on a seven-point Likert scale, with responses ranging from “completely disagree” (−3) to “completely agree” (+3) (Gregor et al., 2006; Ji-fan Ren et al., 2016).
The second, strategic value, refers to the degree of perceived benefits for the organization at the strategic level, as enabling quicker response to change or improving customer relations (Centobelli and Ndou, 2019). It was assessed using three items based on a seven-point Likert scale, with responses ranging from “completely disagree” (−3) to “completely agree” (+3) (Gregor et al., 2006; Ji-fan Ren et al., 2016).
The third, transformational value, refers to the degree of perceived changes in the structure and capacity of a firm as a result of BDA solutions, which serve as a catalyst for future benefits. It was assessed using four items based on a seven-point Likert scale, with responses ranging from “completely disagree” (−3) to “completely agree” (+3) (Gregor et al., 2006; Ji-fan Ren et al., 2016).
The fourth, informational value, refers to the degree to which the user of BDA solutions benefits from better information as improving the management of data or enabling faster access to data. It was assessed using three items based on a seven-point Likert scale, with responses ranging from “completely disagree” (−3) to “completely agree” (+3) (Gregor et al., 2006; Ji-fan Ren et al., 2016).

*3.2.3 Moderating variables*

The moderating and control variables have been assessed using DIANE Bureau Van Dijk databases (Table 3).

*Environmental dynamism*. Environmental dynamism is the rate of instability of the environment, which is the result of changes in the customer preferences, the development of new products, new technology, or the competition (Dale Stoel and Muhanna, 2009). To operationalize this environmental contingency, we levered the approach of Dess and Beard (1984). Following Dale Stoel and Muhanna (2009), we measured environmental dynamism as variability in annual industry sales. Specifically, it was assessed using DIANE Bureau Van Dijk databases, which contain firm and industry data defined at the three-digit Standard Industrial Classification (SIC) industry level (Johnson and Greening, 1999). For each sector, industry-level total sales for five years (from 2010 to 2015) were regressed on the year variable. Dynamism was measured as the standard error of the regression slope coefficient of annual industry sales divided by the industry mean for the five-year period.

*Environmental munificence*. It refers to the extent to which the environment can support sustained growth. Industries that are mature or shrinking are characterized as having low munificence and competition is intense, leading to price wars, which give low-cost producers a distinctive advantage (Dale Stoel and Muhanna, 2009). Industry munificence was assessed using the DIANE Bureau Van Dijk databases. Based on the fact that munificent environments are those which support sustained growth, using data on total industry sales revenues, environmental munificence was measured as the growth rate in annual industry sales over five years (from 2010 to 2015), as measured by the regression slope coefficient divided by average industry sales (Dale Stoel and Muhanna, 2009).

*3.2.4 Control variables*

*Firm size*. We operationalized the firm size with the logarithmic form of the sales of every company.

*Firm age*. We operationalized the firm age with the logarithmic form of the firm age by considering the foundation year.

*Industries*. We operationalized the firm's industry by generating a set of dummy variables, one for each sector. To simplify the readability of the models, we omitted the coefficients of these variables in the Table 7, showing the regression results. Industry code was based on the 1-digit Standard Industry Classification (SIC) level.

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**Table 2. Operationalization of the independent and the dependent variables based on the Likert scale, collected via the questionnaire.**

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**Figure 2. The independent variable, BDA business value, as second order construct and the dependent variables as three separate constructs: financial performance, market performance and customer satisfaction**

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**Table 3. Operationalization of the moderating and control variables collected via the Bureau Van Dijk DIANE database**

### *3.3 The empirical models*

The hypotheses were tested using the dataset of companies that use BDA (38% of companies surveyed), out of the 200 companies received. We tested the moderating effects of the two moderating variables, environmental dynamism and environmental munificence, on the relationship between the business value of big data and firm performance. The independent variables were standardized, since we included the interaction variable, for evaluating the moderation effects in the models.

We have addressed the concern of the reverse causality and the endogeneity of IT investment (Lee et al., 1997; Brynjolfsson and Hitt, 2000; Aral et al., 2006) using instrumental variables (IV) techniques. Specifically, we used a two-stage least-squares (2SLS) regression approach. Thus, we used instruments that must be correlated with BDA business value but not with dependent variables. We employed three IV: the big data Variety, the big data Volume and the big data Velocity questions, available from the first section of the questionnaire, as explained before.

Overall, we run twelve 2SLS models with the IV to verify the moderating effects. $X_t$ is the set of control variables that could influence the performance of a company and each model includes the logarithm of the firm size and the industry dummy variables. These twelve models can be grouped in four subsets.

The first subset refers to the direct effects of the independent variables, considering the moderating variables as independent, on the three dependent variables. The first three models, Model 1 to Model 3, contain as independent variables the control variables and the three first order variables (BDA business value, environmental dynamism and environmental munificence), and as dependent variables respectively financial performance (Model 1), market performance (Model 2) and customer satisfaction (Model 3). They take the following forms:

*Model 1: Financial performance* $= a_1 + b_1$ *BDA business value* $+ b_2$ *Environmental dynamism* $+ b_3$ *Environmental munificence* $+ b_4 X_t + \varepsilon_t$

*Model 2: Market performance* $= a_2 + b_5$ *BDA business value* $+ b_6$ *Environmental dynamism* $+ b_7$ *Environmental munificence* $+ b_8 X_t + \varepsilon_t$

*Model 3: Customer satisfaction* $= a_3 + b_9$ *BDA business value* $+ b_{10}$ *Environmental dynamism* $+ b_{11}$ *Environmental munificence* $+ b_{12} X_t + \varepsilon_t$

The second subset, Model 4 to Model 6, refers to the moderating effect of environmental dynamism on the relationship between the BDA business value and every firm performance investigated. They differ from the previous three model to the extent that they contain as independent variable the interaction effects between the BDA business value variable and the environmental dynamism variable. They take the following forms:

*Model 4: Financial performance* $= a_4 + b_{13}$ *BDA business value* $+ b_{14}$ *Environmental dynamism* $+ b_{15}$ *Environmental munificence* $+ b_{16}$ *BDA business value* * *Environmental dynamism* $+ b_{17} X_t + \varepsilon_t$

*Model 5: Market performance* $= a_5 + b_{18}$ *BDA business value* $+ b_{19}$ *Environmental dynamism* $+ b_{20}$ *Environmental munificence* $+ b_{21}$ *BDA business value* * *Environmental dynamism* $+ b_{22} X_t + \varepsilon_t$

*Model 6: Customer satisfaction* $= a_6 + b_{23}$ *BDA business value* $+ b_{24}$ *Environmental dynamism* $+ b_{25}$ *Environmental munificence* $+ b_{26}$ *BDA business value* * *Environmental dynamism* $+ b_{27} X_t + \varepsilon_t$

The third subset, Model 7 to Model 9, refers to the moderating effect of environmental munificence on the relationship between the BDA business value and every firm performance investigated. They are different to the previous ones, as they contain as independent variable the interaction effects between the BDA business value variable and the environmental munificence variable. They take the following forms:

*Model 7: Financial performance* $= a_7 + b_{28}$ *BDA business value* $+ b_{29}$ *Environmental dynamism* $+ b_{30}$ *Environmental munificence* $+ b_{31}$ *BDA business value* * *Environmental munificence* $+ b_{32} X_t + \varepsilon_t$

*Model 8: Market performance* $= a_8 + b_{33}$ *BDA business value* $+ b_{34}$ *Environmental dynamism* $+ b_{35}$ *Environmental munificence* $+ b_{36}$ *BDA business value* * *Environmental munificence* $+ b_{37} X_t + \varepsilon_t$

*Model 9: Customer satisfaction* $= a_9 + b_{38}$ *BDA business value* $+ b_{39}$ *Environmental dynamism* $+ b_{40}$ *Environmental munificence* $+ b_{41}$ *BDA business value* * *Environmental munificence* $+ b_{42} X_t + \varepsilon_t$

The fourth subset, Model 10 to Model 12, refers to the moderating effect of environmental munificence and dynamism on the relationship between the BDA business value and every firm performance investigated. They show the regression results, including both interaction effects in every model. They take the following forms:

*Model 10: Financial performance* $= a_{10} + b_{43}$ *BDA business value* $+ b_{44}$ *Environmental dynamism* $+ b_{45}$ *Environmental munificence* $+ b_{46}$ *BDA business value* *

*Environmental munificence* + $b_{47}$ *BDA business value* * *Environmental dynamism* + $b_{48}X_t + \varepsilon_t$

*Model 11: Market performance* = $a_{11}$ + $b_{49}$ *BDA business value* +$b_{50}$ *Environmental dynamism* + $b_{51}$ *Environmental munificence* + $b_{52}$ *BDA business value* * *Environmental munificence* + $b_{53}$ *BDA business value* * *Environmental dynamism* + $b_{54}X_t + \varepsilon_t$

*Model 12: Customer satisfaction* = $a_{12}$ + $b_{55}$ *BDA business value* +$b_{56}$ *Environmental dynamism* + $b_{57}$ *Environmental munificence* + $b_{58}$ *BDA business value* * *Environmental munificence* + $b_{59}$ *BDA business value* * *Environmental dynamism* + $b_{60}X_t + \varepsilon_t$

## 4. Analyses and results

### *4.1 Psychometric properties of the measures*

Before running the regressions, we conducted a Confirmatory Factor Analysis in order to verify whether the variables already used in other studies have the appropriate psychometric properties of the measures investigated in this study (Table 4). The loadings of the measures on their respective constructs ranged from 0.672 to 0.880. We consider these loadings satisfactory (Hair et al., 1998). The t-statistic of each factor loading was compounded to verify convergent validity. All the factor loadings were found to be statistically significant, and all the t-values were higher than the cut-off point of 1.980. The overall constructs were meritorious, given that the Kaiser-Meyer-Olkin measure of the sampling adequacy was equal to 0.843 and that Bartlett's test of sphericity gave a statistically significant chi-square value of 1,156 (p-value = 0.001). The recommended reliability levels and Average Variance Extracted (AVE) were also observed. Cronbach's alpha values ranged from 0.650 to 0.839, and the AVE values ranged from 0.516 to 0.676. These values are higher than the acceptability threshold values (Bagozzi and Yi, 1988; Churchill Jr, 1979). These results revealed the presence of convergent validity in the measurement model. Uni-dimensionality was also confirmed by the AVE values (>0.50).

The variance explained by each principal factor was also tested to identify any potential common method bias (Podsakoff and Organ, 1986). Harman's one-factor test showed that the first factor only accounts for 23.542% of the total variance, which indicates that the common method bias would not be a serious problem. Furthermore, the correlation matrix (Table 5) shows that the highest inter-construct correlation is 0.602, while the common method bias is usually evidenced by extremely high correlations ($r > 0.90$) (Bagozzi et al., 1991). Therefore, it is possible to state that the common method bias in this research was not a serious issue.

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**Table 4. Descriptive and psychometric table of measurements**

Table 5 shows the discriminant validity of our variables measured with Likert scales. The square root of AVE was compared for each construct with correlations between each construct and the remaining constructs (Fornell and Larcker, 1981). Each construct shared more variance with its own measurement items than with the constructs of the various measurement items. Therefore, discriminant validity was supported.

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**Table 5. Correlation matrix of the measured scales for discriminant validity evaluation and square roots of the AVE as diagonal elements**

### *4.2 Descriptive statistics*

Table 6 contains the descriptive statistics of the other variables included in the models. Customer satisfaction was the highest firm performance, looking at the mean values of the different firm performances. Financial performance was the second most appreciated outcome, while market performance was the least appreciated aspect. Considering the size of the companies, since we excluded small companies from the very beginning, companies had at least 50 employees and as high as 1,270 employees.

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**Table 6. Descriptive statistics**

### *4.3 Regression results*

We used STATA 14 to conduct the regression analyses. In order to ensure that the multicollinearity effects were not an issue, the Variance Inflation Factor (VIF) was computed for each of the variables by running separate analyses in which one variable was the dependent variable while all the other variables were considered as independent. The VIF values ranged from 5.50 to 5.66. None of the VIF values reached the maximum acceptable level of 10. Thus, multicollinearity did not appear to be an issue.

Table 7 shows the regression results of our 12 models by using 2SLS regression approach with IV. Specifically, there are four sets of regression models. Model 1, Model 2 and Model 3 show that BDA business value leads to an increase of customer satisfaction, market performance and financial performance. Indeed, our hypotheses are on the environmental contingencies.

In our first set of Hypotheses, H1, we formulated that the higher the level of environmental dynamism, the higher the contribution of BDA solutions will be to the three performances of a firm: (H1a) financial performance, (H1b) market performance, and (H1c) customer satisfaction. Results of Model 4, Model 5 and Model 6 show that the interaction effect between business value and environmental dynamism is not significant for any dependent variable. This means that the dynamism of the environment does not have any effect in explaining the impact of business value on firm performance. For this reason, the first set of our Hypotheses H1 were all not supported.

In the second set of Hypotheses H2, we formulated that the higher the level of environmental munificence, the higher the contribution of BDA solutions will be to the three performances of a firm: (H2a) financial performance, (H2b) market performance, and (H2c) customer satisfaction. Results of Model 7, Model 8 and Model 9 show that the interaction effect between BDA business value and environmental munificence was significant for all the three dependent variables. This means that the munificence of the environment strengthens the impact of BDA business value on the three firm performances. For this reason, the second set of Hypotheses H2, H2a, H2b and H2c, were supported.

We additionally made endogeneity tests in order to verify whether the chosen instruments are good or not. First we tested the null hypothesis $H_0$ that the IV are exogenous. Both Durbin (score) statistic and Wu-Hausman statistic in all the models have a statistically significant p-value, which allows to reject the null hypothesis that the IV are exogenous, thus supporting that they are endogenous. Second, we also tested for overidentification restrictions, where the null hypothesis is that the instrument set is valid and the model is correctly specified. The Sargan (score) Chi-squared has a p-value above the significance threshold and therefore the test is not significant. This means that the instruments set was valid.

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**Table 7. Regression results**

## 5. Discussions

In this study, we measured the extent of the translation of the BDA business value into firm performance and our results enrich the previous empirical studies on the subject (Akter et al., 2016; Ji-fan Ren et al., 2016; Wamba et al., 2017a, 2015). Our main theoretical contribution concerns the enrichment of the literature about the integration of the inward looking strategic perspectives, around the RBV, and the outward looking strategic perspectives, around contingency theory. We show the benefits of combining RBV and contingency theories to explain the contribution of BDA solutions to firm performance. The RBV distinguishes business value from firm performance and helps to explain why BDA solutions contribute to the creation of a competitive edge (Wamba et al., 2017a, 2017b). When, inspired by the RBV perspective, we consider the BDA solutions as a firm's resource, we can conclude that the big data is a resource satisfying the necessary conditions for the creation of a competitive advantage: big data can be rare, inimitable and non-substitutable.

Complementary, the contingency theory justifies the moderating role of environmental munificence and dynamism (Dale Stoel and Muhanna, 2009), even if we discovered that only environmental munificent plays a significant role on the impact of big data. Industry-related environmental effects have regularly been recognized as possible important factors playing a moderating role on firm's performances, when looking at the impacts of IT (Li and Ye, 1999). Hence, companies must pay attention to these external variables, in addition to their endogenous mechanisms, in their pursuit of competitive advantage (Burns and Stalker, 1961; Thompson et al., 1992). Given the absence of specific demonstrations of the moderating role of environmental contingencies on firm performance for BDA solutions, we explicitly formulated two distinct set of hypotheses on the moderating role of two environmental contingencies for BDA solutions. To the best of the authors' knowledge, this is the first study to evaluate the importance, in the big data domain, of the moderating effects of environmental munificence and environmental dynamism. On one hand, companies in industries characterized by a munificent market profit the most from their BDA solutions as their solutions further the firms' performances. The business value extracted from these IT solutions will enhance the competitive advantage of the firm in cases of high munificence. Hence, firms in munificent industries have an additional incentive for investing in BDA solutions. BDA solutions could make companies better able to follow growing customer demands. Complementary, the innovation and the experimentation, promoted by BDA solutions, could be more easily converted to competitive advantage in highly munificent markets (Tan et al., 2015; Wamba et al., 2015). Moreover, the possible future orientation of BDA solutions could facilitate the generation of new forward looking strategic initiatives which best match a supporting and growing environment.

On the other hand, and against our expectations, environmental dynamism did not emerge as a significant moderator. We hypothesized that the higher the level of environmental dynamism, the higher the contribution of BDA solutions would have been to firm performance. Results show that the contribution is neither positive nor negative. Indeed, literature helps us explaining our results. Even though several studies (Côrte-Real et al., 2017; Wang et al., 2016) leaded us to hypothesize a positive relationship, some other studies bring divergent views. Indeed, research has noted that IT may hinder a firm's capacity to adapt to radical changes in the environment, due to the rigidity of the fixed physical and technological artefacts of IT systems. Firms are often constrained by the limitations of rigid IT architectures, complex IS and disparate technologies to a point that the organisation is hindered from rapidly adapting to external changes (Van Oosterhout et al., 2006). Beyond the direct technical issues, also the management of IT could lead to unintended firm rigidity in responding to radical environmental changes, like ignoring weak signals (Lu and Ramamurthy, 2011). The role of IT in generating rigidity, rather than agility, in addressing the external contingencies could be particularly prominent in firms having invested in BDA facing dynamic contexts. This may be understood looking at the specificities of the BDA solutions. BDA solutions include high volumes of data, which could be time and cost consuming to accumulate to a satisfactory level. An unexpected change in the environment could make the accumulated volume of data less relevant, making the time and the cost required to accumulate them unrecoverable. Also the capabilities of an organization on big data could potentially be ineffective in highly dynamic environments (Schilke, 2014). When the environment changes, firms reactivate organizational responses that proved successful under similar situations in the past. This implies that unfamiliar states in the external environment are ignored or are treated in a similar manner to some other types of events encountered and understood in the past. When an apparently proven response to an identified problem exists in the organizational memory, experimentation with alternatives becomes less attractive. Overall, different forces oppose, one another, in defining the direction of the moderating influence of environmental dynamism and maybe, at the end, these forces balance, one another, making the influence of environmental dynamism not significant.

In synthesis, BDA solutions fit better in munificent industries, while the performance of BDA solutions is not influenced by turbulent environments. Hence, our integration of the two perspectives of the RBV theory and the contingency theory facilitates the comprehension of the possible fit between BDA, as a firm's resource, and the external contingency of a munificent environment, which accentuates the benefits of the firms' BDA resource. We contribute, hence, to the open debate about the role of industry characteristics and the value of IT resources, showing evidences of the advantages in the combination of the contingency theory with the RBV theory of the firm to explain the performances coming from BDA solutions.

Additionally, we posited that the large possible diversity in the applicability of big data needed a broad definition of firm performance. Hence, we chose to measure firm performance with three different dimensions: financial performance, market performance and customer satisfaction. Our results point out that big data maintains the promise of creating a three-fold firm performance. First, BDA solutions facilitate the entry of a firm onto new markets, the release of innovative products and the possibility of beating competitors. Second, BDA solutions help a company to satisfy its customers with better products and services than the competition. Third, BDA solutions enhance the financial performance of a firm, as far as customer retention, sales growth and profitability are concerned. Nonetheless, managers should be aware of the fact that some differences could emerge, depending on the particular IT artefacts in which they want to invest (George et al., 2014; Lynch, 2008; Mayer-Schönberger and Cukier, 2013; Orlikowski and Scott, 2015; Watson, 2014).

### *5.1 Managerial implications*

Previous research highlighted the need of managers to better understand whether, when, and how to innovate with BDA solutions (Abbasi et al., 2016; Agarwal and Dhar, 2014; Côrte-Real et al., 2017; Erevelles et al., 2016; LaValle et al., 2011; Xu et al., 2016). Several risks have been identified in BDA investments (Akter et al., 2016). The model we proposed provides those managers interested in big data implications (Davenport, 2014; IDC, 2016) a tool to understand the impact of BDA solutions on firm performance, integrating endogenous resources with exogenous conditions. For practitioners this study demonstrates how best to leverage the BDA solutions to achieve, to maintain competitive advantages and it provides support to justify BDA investments. The results indicate that BDA solutions enhance the firm performance according to the environmental features. Our results point out that BDA maintains the promise of creating added value to companies and that this value creation is amplified in munificent industries. Hence, this enhancement is stronger when the market can support sustained growth in demand and have an increasing customer base.

Firms that have not yet decided to adopt BDA technologies can gain a perception of the advantages in terms of firm performances that are possible by adopting and effectively using BDA. Moreover, firms should acquire and develop their BDA solutions in relation to their contingencies. Firms should take into consideration their industry environment to find the satisfactory fit between their BDA investments and the industry characteristics. Our results indicate that managers working in munificent industries are the best placed to invest and profit from BDA solutions.

Complementary, software vendors of BDA can also exploit the results of this study to better segment the market. As far as munificent environments are contingencies that boost the contribution of BDA solutions to firm performances, software vendors should target, first, the munificent industry actors, in their BDA marketing campaigns. On the opposite, the firms in turbulent environments should not be a priority for software vendors, as vendors would have less arguments to convince prospects to adopt BDA solutions.

### *5.2 Limitations and directions for future research*

This study has some limitations that open up interesting opportunities for future research. First, the study had a cross-sectional research design, in which all the measurement items were collected at the same point of time. A longitudinal study could extend this research by capturing the dynamics of the business value of BDA solutions on firm performances. Second, the research employed one data collection method for each portion of data. Multiple sources of data could be used to further verify the proposed research model. On one hand, data about the business value of BDA solutions and firm performance could be obtained from objective sources. On the other hand, data about environmental dynamism and environmental munificence could be gathered via the questionnaire.

## 6. Conclusions

Our study contributes to the understanding of the factors affecting the relationship between BDA solutions and firm performance. We particularly enrich the scientific knowledge around the integration of the RBV theory with the contingency theory, at the crossroads of technology and management sciences. Empirically, we demonstrated the extent to which BDA solutions can provide companies with a competitive advantage and the role played by environmental contingencies. On one hand, we highlighted the moderating and positive influence of environmental munificence on the relationship between BDA business value and firm performance. On the other hand, we stated the absence of a moderating influence of the environmental dynamism on the relationship between BDA business value and firm performance. The study offers evidence that the BDA business value brings higher firm performance where markets are in a growing phase.

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