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Unlocking the drivers of big data analytics value in firms

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ABSTRACT

Although big data analytics (BDA) is considered the next "frontier" in data science by creating potential business opportunities, the way to extract those opportunities is unclear. This paper aims to understand the antecedents of BDA value at a firm level. The authors performed a study using a mixed methodology approach. First, by carrying out a Delphi study to explore and rank the antecedents affecting the creation of BDA value. Based on the Delphi results, we propose an empirically validated model supported by a survey conducted on 175 European firms to explain the antecedents of BDA sustained value. The results show that the proposed model explains 62% of BDA sustained value at the firm level, where the most critical contributor is BDA use. We provide directions for managers to support their decisions on BDA strategy definition and refinement. For academics, we extend BDA value literature and outline some potential research opportunities.

1. Introduction

Following an enormous impact of big data on society, big data analytics (BDA) has recently been described as "the next frontier for innovation" (Shollo & Galliers, 2016) and is drawing the attention from both academic and practitioner communities (Agarwal & Dhar, 2014; Delen & Zolbanin, 2018; Erevelles, Fukawa, & Swayne, 2016). The challenge to extract business value from massive volumes of data has been considered paramount to understand the social environment and the dynamics of firms (Loebbecke & Picot, 2015).

BDA is regularly considered a significant differentiator between high performing and low-performing organizations (Chen, Chiang, & Storey, 2012; Loebbecke & Picot, 2015; Wamba et al., 2017). Although many firms have avidly pursued the value provided by BDA technologies, more than half of BDA initiatives are unable to achieve their strategic goals (Mithas, Lee, Earley, Murugesan, & Djavanshir, 2013). In fact, according to a worldwide survey, 43% of firms obtain little or no benefit from BDA (White, 2015). Although IT value research has been widely assessed in the last decades, academics and practitioners are calling for advances in BDA value research (e.g. Agarwal & Dhar, 2014; Erevelles et al., 2016; Fosso Wamba, Akter, Edwards, Chopin, & Gnanzou, 2015; Günther, Rezazade Mehrizi, Huysman, & Feldberg, 2017), as the current understanding of how firms should proceed to obtain value from BDA technologies remains limited (Barton, 2012; Kwon, Lee, & Shin, 2014; LaValle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011; Loebbecke & Picot, 2015). Also, due to BDA specifics, recent literature has highlighted the need to assess BDA value (Fosso Wamba, Akter, & de Bourmont, 2018; Jeble et al., 2018). For instance, talent management has been discussed as an important enabler of BDA value, as technical skills from these technologies are quite difficult to obtain. Big data analysts need not only to have specific skills (such as problem-solving skills, communication, and people skills) but also knowledge in statistical analysis, machine learning and business context to be able to understand business problems (Davenport & Dyché, 2013). To address this gap, we qualitatively investigate and quantitatively confirm the antecedents of BDA business value in European firm. We explored: *What are the most important antecedents of BDA business value at the firm level*? We make two contributions to the BDA and IT business value literature. First, we find that BDA business value can be provided in three distinct ways, namely sustained, real, and potential value. Second, we recognize BDA use as instrumental in achieving sustained business value from BDA investments.

We organize the remainder of the paper as follows. We first introduce BDA and previous works studying its business value, as well as the field applications associated with BDA. We then outline our mixed methodological approach and report on our results, followed by our findings on the drivers of BDA value. In the discussion section, we explore the theoretical contributions and practical implications of our findings. Finally, we present some inherent limitations and avenues for future research.

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2. Business value of big data analytics

The BDA concept arose from the need to effectively manage big volumes of data in order to improve business insight. Recently, BDA emerged as a field of interest related to business intelligence and analytics research (Gupta, Deokar, Iyer, Sharda, & Schrader, 2018; Kwon et al., 2014; Sivarajah, Kamal, Irani, & Weerakkody, 2017). Mostly grounded in data mining and statistical analysis, BDA can be defined as "*technologies* (*e.g., database and data mining tools*) *and techniques* (*e.g., analytical methods*) *that a company can employ to analyze large-scale, complex data for various applications intended to augment firm performance across various dimensions*" (Chen et al., 2012).

IT business value (Melville, Kraemer, & Gurbaxani, 2004; Tallon & Kraemer, 2007) has been widely studied across various types of IT (e.g. Chuang, 2004; Habjan, Andriopoulos, & Gotsi, 2014; Martins, Oliveira, & Thomas, 2016; Picoto, Bélanger, & Palma-dos-Reis, 2014). When it comes to delivering business value, scholars affirm the recognition of BDA to help firms improving their business processes (Chau & Xu, 2012; Loebbecke & Picot, 2015; Popovič, Hackney, Tassabehji, & Castelli, 2016) or customer experience and satisfaction (Chen et al., 2012; Verhoef, Kooge, & Walk, 2016).

Business value of individual BDA components, such as business intelligence and business analytics, have been the subject of study over the past years (e.g. Elbashir, Collier, Sutton, Davern, & Leech, 2013; Işık, Jones, & Sidorova, 2013; Oliveira, McCormack, & Trkman, 2012; Popovič, Hackney, Coelho, & Jaklič, 2012). Although a plethora of business intelligence and business analytics studies currently exist, scholars call for a more in-depth understanding of BDA value (Loebbecke & Picot, 2015; Popovič et al., 2016; Wamba et al., 2017). Due to their specificities, previous empirical literature has concluded that BDA value should be examined (e.g., (Akter, Wamba, Gunasekaran, Dubey, & Childe, 2016; Chen, Preston, & Swink, 2015; Fosso Wamba et al., 2018)). For example, Chen concluded in his study that BDA use can be leveraged if proper top management lends support, as these tools are also expected to underpin strategic decisions (Chen et al., 2015). Furthermore, other studies highlight the need to focus on quality dynamics, as BDA is fed by big data that requires a certain level of data quality in order to be useful to firms (Fosso Wamba et al., 2018).

3. Research methodology

This study uses a research methodological approach encompassing two phases. First, to explore the BDA antecedents, we performed a Delphi study and final semi-structured interviews. Based on the results of the qualitative research, the authors conducted a multi-country survey and undertook a PLS analysis to validate the conclusions of the research.

3.1. Exploratory phase: Delphi method

The Delphi method employs a group of experts to obtain the most consistent and consensual results (Okoli & Pawlowski, 2004). According to Paré, Cameron, Poba-Nzaou, and Templier (2013), four main methodologies have strongly influenced the Delphi method (Dalkey & Helmer, 1963; Debecq, Van de Ven, & Gustafson, 1975; Linstone & Turoff, 1975; Schmidt, 1997). Due to the purpose of our study, based on the trade-off between theoretical rigor and operational limitations, we choose the methodology outlined by Schmidt (1997). When compared with other methodologies, Schmidt's approach seems to be the most complete and rigorous (e.g., document expert profile; randomization of items in the first round and then by mean rank). We also considered some additional recommendations of other authors (Okoli & Pawlowski, 2004; Paré et al., 2013; Rowe & Wright, 2011).

To conduct the exploratory research, we used the Delphi method (Okoli & Pawlowski, 2004) for several reasons. Firstly, for this type of exploratory research, a Delphi study is an appropriate research design (Akkermans, Bogerd, Yücesan, & van Wassenhove, 2003). It can be especially valuable in cases in which knowledge is incomplete, as is the case of BDA business value (Chen et al., 2012; Erevelles et al., 2016; Mithas et al., 2013). Also, earlier studies have used this method to address similar research questions related to IT managerial practices and effects (Gallego, Luna, & Bueno, 2008; Kasi, Keil, Mathiassen, & Pedersen, 2008). Secondly, the Delphi method is particularly useful in situations where subjective and complex judgments are of interest, as opposed to precise quantitative results (Daniel & White, 2005). Thus, since the task at hand involves identifying the antecedents of BDA value, the Delphi method fits the purpose (Schmidt, 1997). Thirdly, this method allows us to address our research problem, as we are looking for input from experts with years of experience in managing BDA initiatives. Additionally, we used semi-structured interviews as they commonly complement the Delphi approach (Keil, Lee, & Deng, 2013; Okoli & Pawlowski, 2004).

3.1.1. Research process

3.1.1.1. Identification of BDA antecedents. In order to identify the potential antecedents for the creation of BDA value, the experts first suggested a list of variables. The authors consolidated this list and removed the duplicate antecedents. We then sent the list out to the experts for approval, yielding a final list of 23 antecedents (see Table 1). Secondly, we mapped the list of suggested antecedents to variables drawn from the IT business value literature to allow this research to serve as an input for a quantitative study. For the selection of the variables in the literature, three criteria were used: (1) IT business value factor, (2) statistical significance to explain IT business value, and (3) discussed and agreed with a first expert panel.

3.1.1.2. Design of the Delphi questionnaires. Based on the list of factors selected, we designed an online questionnaire in which experts were asked to rate those factors on a 7-point numerical scale (1 = Strongly Disagree and 7 = Strongly Agree). To enhance the reliability of the study and to avoid ambiguity the Delphi questionnaires and the task instructions were pre-tested with a sample of respondents comprising BDA academics and practitioners who were not on the expert panel but possessed similar characteristics.

3.1.1.3. Selecting the expert panel. To ensure the quality of the results, choosing the appropriate experts is the key part of the study (Paré et al., 2013). In order to prevent influential behaviors among experts, anonymity was preserved. The identification of experts for the Delphi panel was done using a multiple-step approach suggested in the literature (Okoli & Pawlowski, 2004). We prepared a list of background and skills based on a "knowledge resources nomination worksheet." The authors used personal contacts of as the initial communication point. We implemented the "snowball" sampling method (Skulmoski, Hartman, & Krahn, 2007) to identify other potential experts to be included in the study. Considering that the success of the Delphi technique relies upon the use of informed opinion, a random selection process was not used to select participants. The main selection criteria for inviting experts to participate in our study were years of business intelligence and analytics experience (over the five years), their job position and the number of big data projects implemented. As suggested by Hsu and Sandford (2007), the authors explained the purpose of the study as well as the procedures, in order to minimize the non-response rate. Of the 34 invitations, 22 candidates accepted, which represented a participation rate of 65%. Linstone and Turoff (1975) considered this rate ideal.

Twenty-two experts from four different countries composed the selected panel. An overview of the expert panel profile is in Table 2. We created a highly qualified expert panel in the BDA field: 54% of the participants have more than ten years of experience, with 18% having more than twenty years' experience.

Table 1
Description of BDA antecedents.

Antecedent	Source	Description
Analytical capabilities	(Popovič et al., 2012)	Represents the provision of analytical capabilities to business (e.g. querying, online analytical processing, reporting, dashboards, data mining, etc.).
Analytical decision-making culture	(Popovič et al., 2012)	It refers to the way the decision-making process is established, based on information provided by BDA to support decisions.
BDA applications	(Sher & Lee, 2004)	It refers to the type and the number of applications related with BDA used in the organization (e.g. data warehousing, data mining tools, sentiment analysis, statistical NPL, Hadoop, etc.).
BDA business interaction	(Tallon & Kraemer, 2007)	It refers to the extent to which BDA has an executive participation in the strategic planning process and involvement in resolving business issues.
BDA use	(Tallon, 2007)	It refers to the extent to which BDA applications are used to support different activities such as: supplier relations, production and operations, product and service enhancement, marketing and sales and customer relations.
Collaboration	(Slater & Narver, 2000)	It enables an organization to generate intelligence with and from other organizations/individuals about new opportunities or means of creating value through BDA applications.
Dynamic capabilities	(Sher & Lee, 2004)	It refers to an organization's ways of responding in a rapidly changing environment.
Environmental volatility	(Tallon & Pinsonneault, 2011)	Environmental volatility is defined as the frequency and extent of change in critical market variables.
Experimentation	(Slater & Narver, 2000)	Experimentation means trying ideas about ways for creating value that are outside of the organization's normal routines, evaluating them and striving for consensus on the meaning of the results using BDA.
Firm agility	(Tallon & Pinsonneault, 2011)	It refers to the speed with which firms can detect and respond to environmental threats and opportunities.
Firm size	(Zhu & Kraemer, 2005)	It is defined by the number of employees in the organization.
IT business experience	(Bhatt & Grover, 2014)	It refers to the extent to which IT groups understand business.
IT infrastructure sophistication	(Elbashir et al., 2013)	It refers to the degree of sophistication of IT infrastructure and BI-related infrastructure to allow the correct performance.
Management of endogenous knowledge	(Sher & Lee, 2004)	It refers to the ability to manage the internal knowledge of the company.
Management of exogenous knowledge	(Sher & Lee, 2004)	It refers to the ability to manage the external knowledge of the company (customers, suppliers, and competitors).
Managerial capabilities	(Fink & Neumann, 2009)	It is the ability of BDA unit to provide management services (e.g. planning, project management), architecture and education services (e.g. training, management education) and others (e.g. identify/test new technologies for business purposes).
Market-focused intelligence	(Slater & Narver, 2000)	Market-focused intelligence generation strategy focuses on acquiring information about customers' expressed and latent needs, and competitors' capabilities and strategies.
Operational managers' shared knowledge	(Elbashir et al., 2013)	It refers to the ability of managers at the operational level to share knowledge provided by BDA applications.
Quality of IT infrastructure	(Bhatt & Grover, 2014)	It refers to the ability to share information across different functions, innovate, and exploit business opportunities, and the flexibility to respond to changes in business strategy.
Standardized business processes	(Slater & Narver, 2000)	It is represented by the need for standardized business processes that can be refined, based on employee input, in order to reduce costs and improve productivity.
Strategic alignment between IT and business	(Tallon & Kraemer, 2007)	It is represented by the interaction or fit between IT and business strategy. Alignment is a product of shared understanding between IT and business managers.
Strategic role of BDA	(Tallon & Kraemer, 2007)	Refers to the extent to which BDA facilitates critical changes to business processes, enables business improvement and facilitates strategic leadership through innovative applications.
Time since adoption	(Elbashir et al., 2013)	It refers to the time since adoption of BDA applications considering the knowledge and experience that organizations gain from working with BDA over time.

3.1.2. Data collection and analysis

Regarding research design, we carefully planned the Delphi process based on Schmidt (1997) recommendations. The survey was conducted over a period of four months. Concerning the data collection process, a Delphi study should be performed in three steps: brainstorming, narrowing down and ranking. We decided to exclude the narrowing phase based on our research goal and the number of items (Schmidt, 1997). Last, in the ranking process, Kendall's coefficient of concordance (W) was calculated to assess the degree of consensus among the panelists (Schmidt, 1997). We conducted two subsequent rounds to achieve a reasonable degree of consensus. Regarding the data analysis process and considering the ranking of antecedents on an ordinal scale, we decided to use a set of measures of tendency, dispersion, association and non-parametric statistics (Okoli & Pawlowski, 2004; Paré et al., 2013; Schmidt, 1997). We used a complementary approach to assure not only the group consensus but also the stability of the results since consensus measurement is considered a valuable component of data analysis. We performed semi-structured interviews by telephone with four panel experts after the Delphi study had finished to understand in-depth the relative importance of BDA antecedents. The experts were asked to justify (1) why top BDA antecedents are so important to manage BDA strategies in organizations and (2) how these top antecedents can be effectively acquired and developed.

3.1.3. Results

Table 3 shows the evolution of the factors during the Delphi study sorted by their position in the final round. This position was obtained using the average rank of each antecedent. For each round, we present the number of respondents (N), Kendall's coefficient of concordance (W) and Spearman's rank-order correlation coefficient (Spearman's *rho*). The average rank (AVG Rank), standard deviation (SD), and rank position are shown for the 23 variables. The study terminated at the third round with a total of 15 respondents, 68% of the initial group; a $W > 0.50$ and a Spearman's rho = 0.937.

In the first round, 22 BDA experts completed the survey (75% response rate). The most important factors ranked were BDA use and strategic role of BDA (AVG rank > 6). The highest standard deviation reached was 1.47 in the BDA capabilities' factor, which indicates a lack of consensus among experts. Over three consecutive rounds, we received 49 useful answers that resulted in Kendall's W of 0.52, which represents a moderate degree of consensus (Schmidt, 1997).

We then assessed the stability of the results by examining the measures of the central trend (such as the average ranking between rounds), dispersion (standard deviations) association and group comparison between rounds 2 and 3. By analyzing the average ranking differences between rounds, we concluded that there was a degree of stability between them. To find out more, we calculated measures of dispersion for the rank scores. To determine whether any BDA

Table 2
Panel demographic profile.

Participant profile	
Industry	7
Academic	3
Consultant	8
Software vendor	2
Mixed profile (academic and industry)	2
Industry sector (NACE code)	
D – manufacturing	2
J – financial intermediation	7
L – public administration	4
M – education	3
O – other services	6
Years of experience	
5–10	10
10–15	6
15–20	2
> 20	4
Job position	
Head of IT/BI/information	4
Senior manager	6
Project manager	6
Program manager	1
Manager	3
Researcher	2
Education	
Advanced graduate work or Ph.D.	8
Master's degree	14

antecedents were particularly controversial, we examined the standard deviations to provide a more precise way to measure rank score consensus. Overall the majority of BDA antecedents reduced their dispersion across the rounds.

To finalize the consensus measurement, we applied association measures. Since the choice of an association measure depends on the type of scale and the sample size (DeLeo, 2004), we chose to use Spearman's rank-order correlation coefficient (Spearman's *rho*), in order to measure whether consensus was being achieved between rounds. A coefficient of 0.937 was obtained, meaning we achieved a high degree of consensus.

Lastly, we performed a complementary analysis to understand the evolution of the factors' positions between the rounds better (see Fig. 1). It is clear that three groups of factors arise from the 23 factors (represented by three different layers in Fig. 1).

Although their positions changed across rounds, those three groups maintain the same composition. This means implies we reached both consistency and concordance in the three rounds. We observed that 17% of the antecedents (4/23) maintained their positions from Round 1 to Round 2. From Round 2 to Round 3, all the antecedents changed their positions very little which indicates a higher level of concordance. In addition, we observed the changes in the antecedents' rankings inside the three groups, which also reinforce the level of concordance.

By observing the results of the third round, a three BDA value clusters (namely sustained, real and potential value) were defined based on the experts' input. The first six factors were considered crucial to obtain sustained business value and consequently achieve a competitive advantage. This set of elements were deemed to be strategic, as their combination imply to create internal capabilities (dynamic capabilities, agility) strategically, and conditions (strategic alignment between business and IT, strategic role of BDA) to be able to fully extract business value based on BDA use and deal with external pressures (environmental volatility). The creation of these vital conditions occurs if supported by effective intermediate management. In this sense, experts argue that the real business value takes shape with the implementation of innovative practices. Hence, firms need to properly set standardized business processes to be able to take advantage of BDA tools. The elicitation of business requirements implies stabilization to be automated by this type of tools. Besides, innovative practices might arise from knowledge management (e.g., experimentation, collaboration, operational managers shared knowledge and market focused intelligence). Lastly, the creation of this innovative environment is only possible if supported by operational conditions. The experts categorized these conditions in the following types: technological characteristics (such IT infrastructure sophistication, quality of IT infrastructure, BDA applications), technical skills (BDA business interaction, IT business experts, BDA capabilities), managerial skills (managerial capabilities),

Table 3
Results of ranking rounds.

Factors	Round 1			Round 2			Round 3		
	AVG rank	SD	Rank	AVG rank	SD	Rank	AVG rank	SD	Rank
Dynamic capabilities	5.95	1.13	4	6.09	0.87	2	6.67	0.49	1
Firm agility	5.91	0.87	5	5.86	0.83	5	6.60	0.51	2
Strategic alignment between IT and business	5.82	1.05	7	6.05	0.79	3	6.47	0.64	3
Strategic role of BDA	6.23	0.69	2	6.32	0.72	1	6.40	0.74	4
BDA use	6.27	1.08	1	5.91	0.68	4	6.27	0.88	5
Environmental volatility	6.00	0.93	3	5.82	0.73	6	6.07	0.70	6
Standardized business processes	5.68	1.21	10	5.68	0.84	8	6.00	0.85	7
Collaboration	5.86	0.99	6	5.55	0.86	10	5.87	0.92	8
Market-focused intelligence	5.50	1.14	14	5.73	0.77	7	5.80	0.68	9
Operational managers' shared knowledge	5.77	1.15	8	5.59	0.85	9	5.80	0.77	10
Experimentation	5.64	1.22	11	5.41	0.96	11	5.73	1.03	11
BDA capabilities	5.55	1.47	13	5.32	0.95	13	5.67	0.82	12
IT infrastructure sophistication	5.32	1.04	17	5.18	0.39	15	5.60	0.91	13
Analytical decision making culture	5.36	1.00	16	5.23	0.92	14	5.53	0.64	14
BDA applications	5.73	1.03	9	5.36	0.85	12	5.47	0.83	15
Quality of IT infrastructure	5.09	1.19	18	5.00	1.02	17	5.27	0.96	16
BDA business interaction	5.59	1.01	12	5.14	0.71	16	5.20	1.01	17
Management of exogenous knowledge	5.38	1.28	15	4.95	0.84	18	4.73	1.16	18
Management of endogenous knowledge	4.55	0.96	22	4.77	0.92	20	4.67	1.05	19
IT business experts	4.68	0.89	21	4.59	0.91	21	4.33	1.07	20
Managerial capabilities	5.05	1.40	19	4.86	1.08	19	4.20	0.77	21
Time since adoption	4.73	1.42	20	4.32	1.21	22	4.13	0.64	22
Firm size	4.14	0.89	23	3.91	0.87	23	3.80	0.86	23
Respondents number (N)	22			22			15		
Kendall (W)	0.25			0.34			0.52		
Spearman's Rho	–			0.901			0.937		

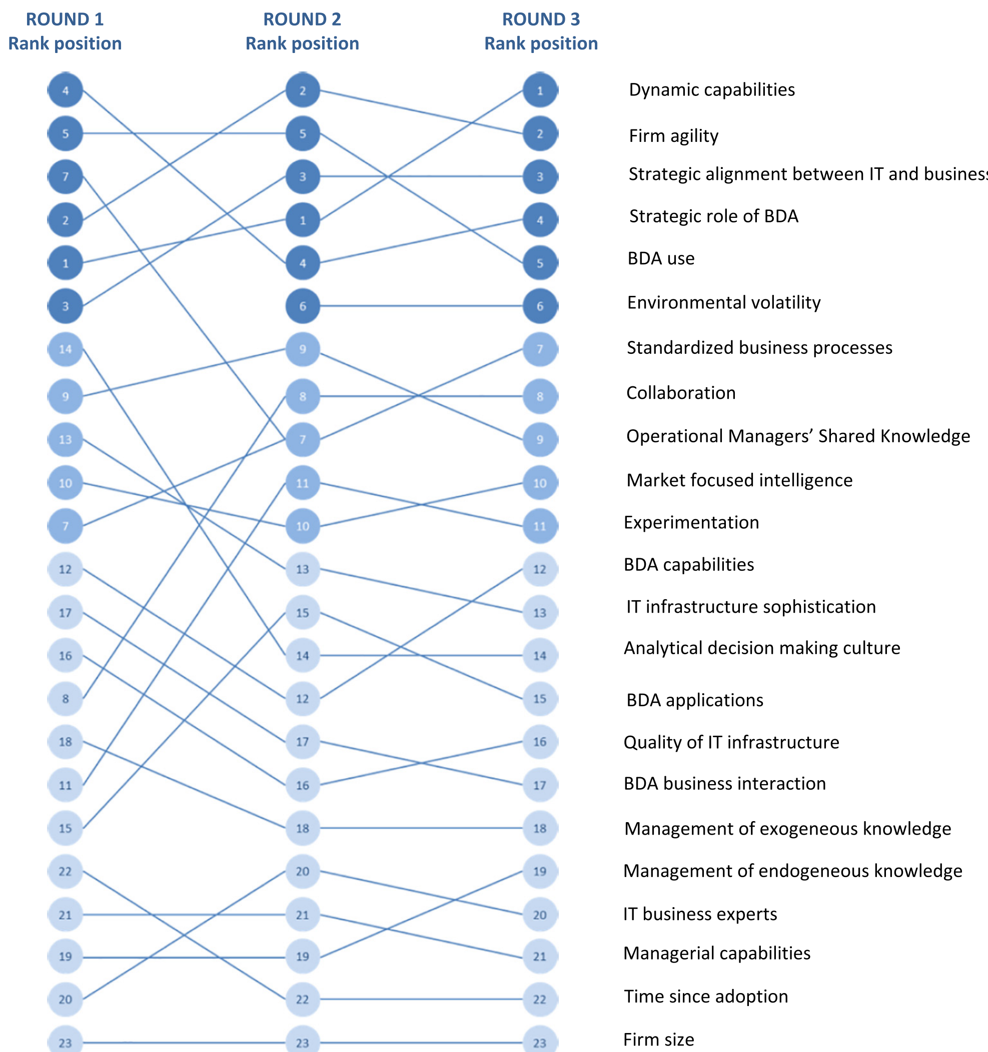

Fig. 1. Rank position of factors in rounds.

cultural conditions (analytical decision-making culture, management of exogenous and endogenous knowledge) and organizational characteristics (firm size, time since adoption). Therefore, we propose a value model in which three types of business value can be observed and developed (see Fig. 2).

3.2. Confirmatory phase: multi-country survey and PLS analysis

Earlier studies have looked at the role of Delphi, not as a stand-alone approach, but as a method that may be complemented by other approaches, or that may contribute as input to others (Rowe & Wright, 2011). To overcome Delphi's limitations, and reinforce and generalize our results, we combined the qualitative Delphi research with a quantitative survey. A mapping work between the antecedents suggested by experts and described in the literature was done during the Delphi study, making this quantitative extension possible. Due to survey size limitations and the strategic focus of this study, only the first set of BDA antecedents for sustained business value selected by the experts in the final round was used to define hypothesis to our conceptual model. Therefore, in light of the strategic management of BDA initiatives, we refine our quantitative research and posterior guidance for academics and researchers.

The authors postulated the following hypotheses as presented in Fig. 3:

H1. Dynamic capabilities positively affect the creation of BDA sustained value.[1]

H2. Strategic alignment between business and IT positively affects the creation of BDA sustained value.

H3. Strategic role of BDA positively affects the creation of BDA sustained value.

H4. BDA use positively affects the creation of BDA sustained value.

H5. Environmental volatility negatively affects the creation of BDA sustained value.

3.2.1. Measurement

The confirmatory phase began by performing a multi-country survey of European organizations from several industries in order to test the model (Fig. 3) and the related hypotheses. The survey instrument design lay on the foundational recommendations from Moore and Benbasat (1991.) Concerning content validity, five established academics from IS field and two language experts reviewed each item of the questionnaire, assessing its content, scope, and purpose (Brislin,

[1] To avoid redundancy in the model, as agility is considered to be one specific dynamic capability, only the variable of dynamic capabilities was considered in the model.

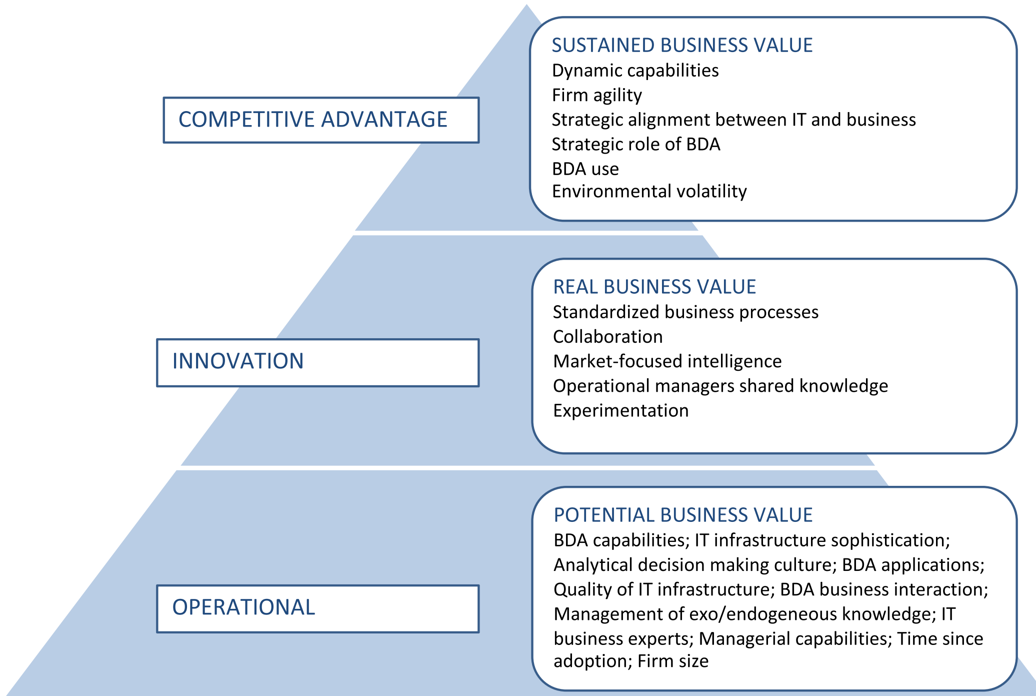

Fig. 2. BDA business value framework.

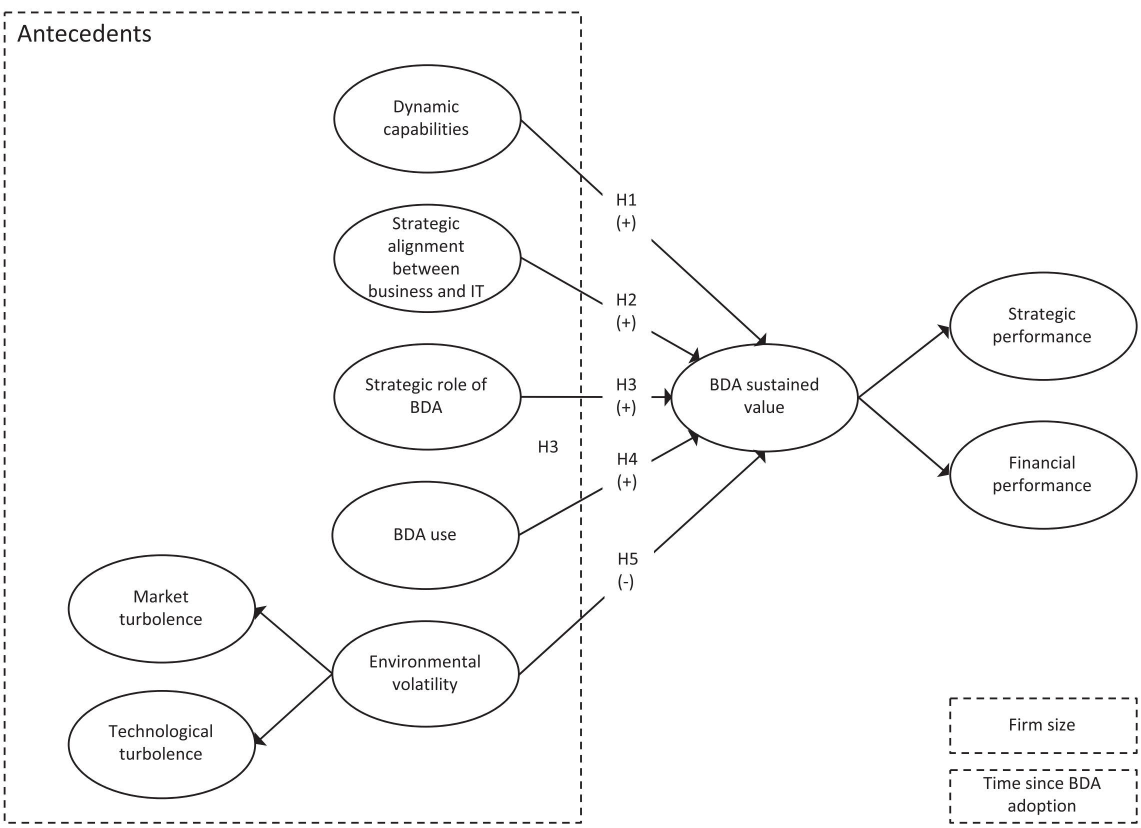

Fig. 3. Conceptual model – BDA sustained value.
Note: BDA sustained value is operationalized by the construct "Competitive advantage".

1970.) We ran a pilot test on a group of 20 executives who did not participate in the Delphi study in an effort to improve readability of the questionnaire.

The survey instrument and measurement items appear in Appendix A.

3.2.2. Data collection

An online survey was sent out in late 2016 to 500 executives of

Table 4
Sample composition.

Sample characteristics (n = 175)	Observations	(%)
Respondent position		
IT executive		
Chief information officer (CIO)	22	12.5%
IT director	26	14.8%
IT manager	32	18.2%
Other IT executive	23	13.1%
Business executive		
Chief financial officer (CFO)	19	10.9%
Business manager - strategic planning	18	10.3%
Central operations officer (COO)	14	8.0%
Other business executive	21	12.0%
No. of employees		
< 50	14	8.0%
50–250	76	43.4%
> 250	85	48.5%

Notes: (1) The firm size is categorized based on European enterprises size classification; (2) The industries of activity are in accordance with NACE (European standard classification of productive economic activities).

European firms, using a mailing database provided by Dun & Bradstreet. A set of criteria was used to ensure data quality: strong knowledge of the organizational strategy, more than five years of experience in BI&A/BDA initiatives, and holding an IT/business executive or management position in the firm. An overall 35% response rate was achieved, obtaining 175 usable responses. The sample composition is in Table 4. To test for non-response bias, we compared the early and late respondent groups using a Kolmogorov-Smirnov test (Ryans, 1974) and did not find any significant differences. The authors conducted a factorial analysis of all indicators to perform an assessment of common method bias. The first extracted factors explain 28.4% of variance, which means common method bias is unlikely in the sample (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003).

3.2.3. *Results*

This study uses partial least squares (PLS) to estimate the conceptual model, as this method allows us to examine the validity of the constructs. As our sample is ten times the number of the largest number of structured paths directed to a particular construct (Gefen & Straub, 2005), we considered this technique to be adequate. First, we examined the measurement model to assess reliability and validity. Finally, we tested the structural model.

3.2.3.1. Measurement model. As all constructs in the measurement model are reflective, they include the assessment of indicator reliability, internal consistency, convergent validity, and discriminant validity. Indicator reliability was evaluated based on the criteria that the loadings should be > 0.70 and that every loading < 0.4 should be eliminated (Henseler, Ringle, & Sinkovics, 2009). Thus, the authors eliminated eight items (SA1-2, USE1, 4-5, MT2-3, T1.) As the loadings are above 0.70, the instrument presents good indicator reliability (Table 5.) We used average variance extracted (AVE) to assess convergent validity. According to literature, the AVE should be > 0.5 (Fornell & Larcker, 1981; Henseler et al., 2009). Table 6 illustrates the fulfillment of this criterion, which ensures convergent validity. Lastly, discriminant validity was tested based on two criteria: (i) the loadings should be larger than the cross-loadings, confirmed in Table 5; (ii) the square root of AVE should be greater than the correlations with other latent variables (Fornell & Larcker, 1981). Table 6 shows that the square roots of AVEs (in bold) are higher than the correlation between constructs. All the constructs provide evidence of acceptable discrimination. As all the criteria required for the measurement model are met, the structural model can be estimated.

3.2.3.2. Structural model. Following Hair, Ringle, and Sarstedt (2011) five-step approach, the partial least squares structural equation model was assessed. First, collinearity was analyzed by observing the VIF indicator. The results suggest minimal collinearity in all the constructs, as the highest VIF is 1.86. This factor means the predictors in the structural model do not suffer from this issue. In order to test the hypotheses, the level of significance in path coefficients was performed using the bootstrapping technique (Hair et al., 2011; Henseler et al., 2009) with 5000 iterations of re-sampling, with each bootstrap sample composed by the number of observations (i.e., 175 cases). By following the experience of (Hair Jr, Hult, Ringle, & Sarstedt, 2013), we used the no 'sign' change option to ensure more conservative outcomes. Fig. 4 shows the model estimation. The proposed model explains 62% of the variation of BDA sustained value in firms, which is considered to be adequate (Chin, 1998; Henseler et al., 2009). With the exception of strategic role of BDA (H3) ($\hat{\beta} = -0.138$; $p < 0.01$), dynamic capabilities (H1) ($\hat{\beta} = 0.239$; $p < 0.01$), strategic alignment between business and IT (H2) ($\hat{\beta} = 0.193$; $p < 0.01$), BDA use (H4) ($\hat{\beta} = 0.316$; $p < 0.01$) and environmental turbulence (H5) ($\hat{\beta} = -0.254$; $p < 0.01$) are statistically significant. Then, f^2 and Q^2 effect sizes were also calculated. The majority of the values of f^2 effect size are considered low. Finally, based on a blindfolding procedure, all Q^2 values are above zero, which means the model has predictive power concerning the dependent variables.

4. Discussion

This study allowed us to understand that the most important antecedents for BDA value are related to business value sustainability. Organizational leaders are concerned about not only exploiting the growing amount of data but also maintaining the competitive advantage that BDA can offer. Thus, dynamic capabilities were considered by the Delphi experts as the most important antecedent to be considered to create organizational business value (#1). The ability to respond rapidly to changes means the organization is not only able to provide BDA tools but is also able to use them and enhance its flexibility to adapt to external changes. Earlier studies concluded that DC led to IT business value (Lin & Wu, 2014; Sher & Lee, 2004). Specifically, BDA can enhance DC and lead to business value creation (Wamba et al., 2017). One example of business processes that are benefiting from the use of BDA is supply chain/delivery route optimization. The way Amazon manages and anticipates its shipping provides a good example of BDA (Erevelles et al., 2016). Also, BDA can improve business processes in the area of human resources management. For example, Sociometrics Solutions puts sensors into employee name badges to detect social dynamics in the workplace. The sensors detect how employees move around the workplace, with whom they speak, and their tone of voice. With this type of analysis, Bank of America was able to understand that their top performing employees at the call centers were those who took breaks together. Consequently, they instituted group break policies and their performance improved by 23% (Marr, 2017). Although DC can significantly optimize core business processes, cultural factors (e.g., managerial intervention type) should be taken into consideration when these readjustments are made. Firm agility, which is a specific dynamic capability, was considered to be the second major challenge to be met (#2). Similarly, earlier literature reports that firm agility can help to acquire sustainable competitive advantages (Chen et al., 2014; Côrte-Real, Oliveira, & Ruivo, 2017b; Tallon & Pinsonneault, 2011). Distinguishing between agility and experimentation is important. While experimentation is needed to provide BDA real value, it can only provide a temporary competitive advantage (e.g., automate a particular business analysis). By experimentation, we can understand potential improvements that allow us to comprehend the market behavior better. To obtain a sustainable competitive advantage, a firm need to have consecutive and successful experimentations to be able to define a strategy. That strategy will allow to critically look at business processes and holistically improve them, which consequently

Table 5
Loadings and cross-loadings for the measurement model.

		Item	DC	SA	SR	USE	MT	TT	FP	SP
Dynamic capabilities		DC1	0.817	0.516	0.390	0.495	−0.124	−0.256	0.446	0.499
		DC2	0.790	0.302	0.370	0.262	−0.018	−0.130	0.245	0.297
		DC3	0.759	0.238	0.181	0.065	−0.109	−0.256	0.236	0.275
		DC4	0.685	0.205	0.261	0.003	0.007	−0.094	0.118	0.207
Strategic alignment between IT and business		SA3	0.347	0.869	0.280	0.663	−0.172	−0.242	0.496	0.569
		SA4	0.430	0.861	0.331	0.392	−0.045	−0.147	0.345	0.406
		SA5	0.443	0.825	0.310	0.341	−0.038	−0.163	0.257	0.334
Strategic role of BDA		SR1	0.400	0.248	0.695	0.199	−0.132	−0.097	0.003	0.120
		SR2	0.348	0.286	0.829	0.252	−0.037	−0.150	0.057	0.081
		SR3	0.363	0.342	0.961	0.353	−0.157	−0.200	0.175	0.275
BDA use		USE2	0.331	0.585	0.353	0.948	−0.271	−0.221	0.571	0.563
		USE3	0.341	0.517	0.297	0.942	−0.300	−0.293	0.525	0.552
Environmental volatility	Market turbulence	MT1	−0.156	−0.146	−0.135	−0.387	0.824	0.499	−0.316	−0.350
		MT4	−0.008	−0.046	−0.105	−0.110	0.825	0.503	−0.261	−0.371
	Technological turbulence	TT2	−0.177	−0.154	−0.172	−0.099	0.491	0.887	−0.199	−0.275
		TT3	−0.287	−0.246	−0.176	−0.374	0.596	0.908	−0.513	−0.603
BDA sustained value (competitive advantage)	Financial performance	FP1	0.333	0.371	0.074	0.571	−0.358	−0.420	0.950	0.728
		FP2	0.388	0.453	0.159	0.486	−0.323	−0.362	0.949	0.665
		FP3	0.401	0.476	0.161	0.593	−0.317	−0.370	0.950	0.704
	Strategic performance	SP1	0.522	0.493	0.265	0.506	−0.339	−0.441	0.584	0.840
		SP2	0.341	0.464	0.159	0.499	−0.472	−0.498	0.719	0.932
		SP3	0.406	0.500	0.225	0.590	−0.365	−0.406	0.681	0.927

create organizational capabilities such agility. BDA can support decision making and help to recognize business opportunities. In this sense, recent literature concluded that BDA technologies facilitate internal and external knowledge management which helps firms to create organizational agility (Côrte-Real, Oliveira, & Ruivo, 2017a). Firms are using BDA tools to store and share knowledge, which allows improving organizational knowledge efficiently. Agility emerges from effective knowledge management by enhancing responses to business problems and use of BDA by automating business processes (Cai, Huang, Liu, Davison, & Liang, 2013). The use of these tools allows converting knowledge into new routines which will inevitably improve firm agility. Hence, this specific capability is observable in various ways: by sensing business opportunities and threats (e.g., reacting to market changes such new products or services); discover new strategies (e.g., expanding into new markets) and by adjusting to the new conditions of the technological environment (e.g., new technology adoption) (Côrte-Real et al., 2017a). Regarding the strategic alignment between IT and business (#3), another expert justified that "*the organizational re-configurations to unlock information scanning capability of the firm is an antecedent for further synchronize at the operational level the process approach to BDA based on the balance of business goals and IT unit*". In this matter, Tallon and Pinsonneault (2011) stated that firms are successful not only because they can analyze more and better data but because they have leadership teams pursuing clear business goals based on the technological initiatives. Specifically, in the BDA field, this alignment depends on the visionary leadership, which helps to synchronize the BDA capabilities with the business goals (Akter et al., 2016). The lack of alignment (mismatch between the organization's existing culture to take decisions and BDA capabilities utility) can erode a firm's performance.

Other strategic factors should be considered, such as the extent to which BDA facilitates strategic leadership and business improvement (#4). Consistent with this, Akter et al. (2016) concluded that BDA needs to have a strategic role in the organization to be able to contribute to performance improvement and consequently to the creation of business value. BDA usage (#5) can be seen as the formalization of business value since it can support different activities such as supplier relations, production and operations, product and service enhancement, marketing, and sales/customer relationship. In this sense, several authors have empirically demonstrated the impact of usage in business value creation (Chen, Preston, & Swink, 2016; Erevelles et al., 2016; Wamba et al., 2017). However, the way it is used is fundamental to extract benefits effectively. Tipp24 AG is a platform for placing bets on European lotteries and making predictions. The company uses BDA tools to analyze billions of transactions and hundreds of customer attributes and to develop predictive models that target customers and personalize marketing messages on the fly. This technique led to a 90% decrease in the time it took to build predictive models (Stedman, 2013.)

Lastly, the level of environmental volatility in the organization has been included (#6); it is the final factor which should be considered to achieve sustainable business value and consequently competitive advantage. By adopting BDA as a firm-level innovation, organizations are able to extract greater value and awareness in securing sustainable advantages (Kwon et al., 2014). This sustainability depends not only on

Table 6
Correlation matrix, composite reliability (CR) and square root of AVEs.

	Composite reliability (CR)	Average variance extracted (AVE)	DC	SA	SR	USE	MT	TT	FP	SP
Dynamic capabilities (DC)	0.849	0.584	**0.764**							
Strategic alignment between IT and business (SA)	0.888	0.726	0.463	**0.852**						
Strategic role of BDA (SR)	0.872	0.698	0.412	0.354	**0.835**					
BDA use (USE)	0.944	0.894	0.355	0.583	0.345	**0.945**				
Market turbulence (MT)	0.809	0.680	−0.100	−0.116	−0.146	−0.301	**0.824**			
Technological turbulence (TT)	0.892	0.805	−0.261	−0.225	−0.194	−0.271	0.608	**0.897**		
Financial performance (FP)	0.965	0.902	0.394	0.456	0.138	0.580	−0.350	−0.405	**0.950**	
Strategic performance (SP)	0.928	0.811	0.464	0.538	0.237	0.590	−0.437	−0.498	0.737	**0.901**

Notes: (a) Diagonal elements (in bold) are square root of average variance extracted (AVE), (b) Off-diagonal elements are correlations.

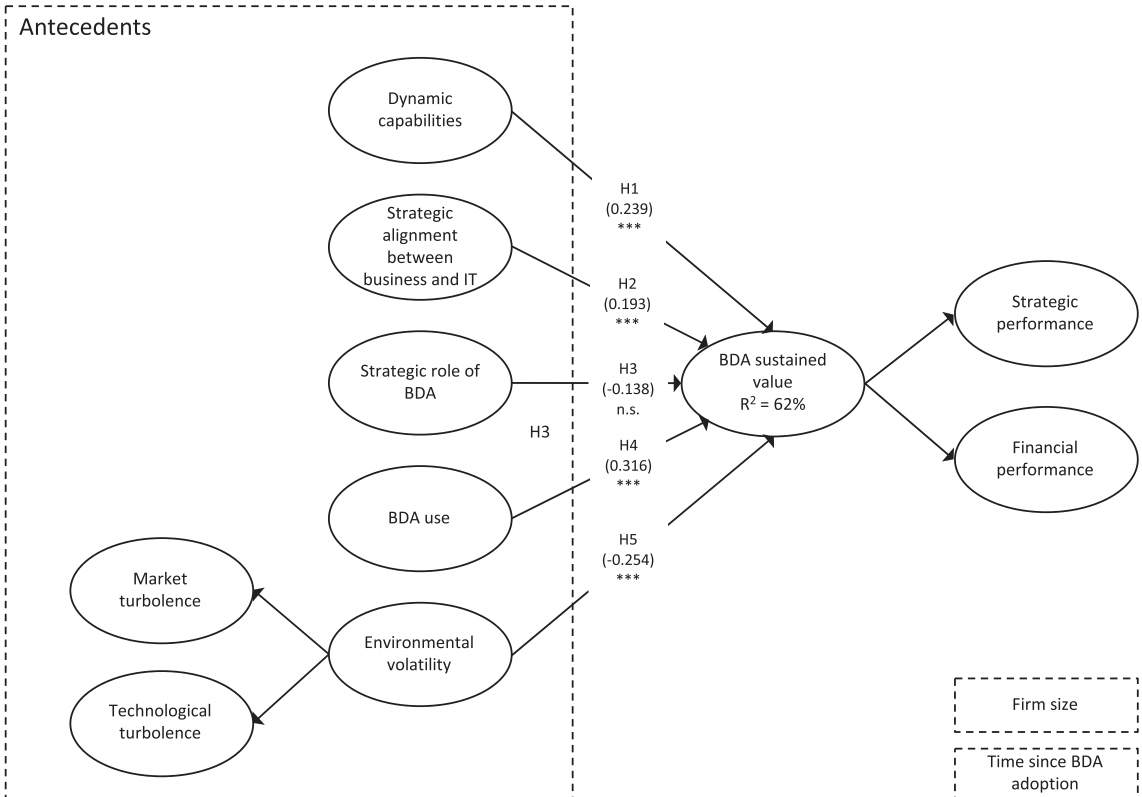

Fig. 4. Estimated model – BDA sustained value.

the internal context but also on the external conditions and can be seen as a control. The environment context was considered to be crucial to manage the competitiveness in the organization brought by IT applications (Pavlou & El Sawy, 2011; Tallon & Pinsonneault, 2011). Specifically, in the BDA field, it can moderate the impact on the creation of dynamic capabilities (Chen et al., 2016). The external context such as the global economic situation, market pressures, new business opportunities, adoption of political regulations, and public images can influence decisions about organizational big data (Gupta et al., 2018). For example, most industries and governments have regulations that can affect the way firms use, share, and retain certain data. There are policies such as the European Union's General Data Protection Regulation (GDPR) and the personally identifiable information (PII) rules in the financial services industry, which require specific processes to be collected and analyzed. Consequently, this changes the logic of how companies are organized.

The results show that experts believe in a top-down approach since the strategic factors were ranked first, followed by managerial and operational factors respectively. This means that it is crucial to have a BDA strategy and the top management must motivate it. Otherwise, the BDA program will most likely fail. This type of program involves changing cultural practices inside each organization. Organizations need to learn to be aligned with the analytical and data-driven culture. We conclude that the organization of BDA factors are according to the types of value they can provide to the organization. We cannot conduct BDA without a strategic business direction. It will waste resources, and the risk of creating widespread skepticism about the BDA real value is severe (LaValle et al., 2011). Also, in a study conducted by MIT Sloan Management Review (Kiron & Shockley, 2011), a top-down approach was considered critical to maintaining the business value provided by BDA.

Although the results are convergent in both parts of the study (Delphi and survey), there are some differences in terms of the level of contribution of antecedents to BDA sustained value. Regarding importance, Delphi and the survey provide different “rankings” (see Table 3). Although DC are considered important in both parts of the study, BDA use is the antecedent that best explains BDA sustained value. The use of BDA applications can be real especially valuable for areas such as Production & Operations (P&O) and Product and Service enhancement (PSE). This conclusion is in line with a recent survey performed Cap Gemini (Toonen, Kanthadai, & Jones, 2016), in which a big data director from a European consumer goods company stated that there is no value in data analytics unless it can be actually used to derive actionable insights from it. Also, Côrte-Real et al. (2017b) concluded that BDA use in P&O and PSE areas could be very beneficial for European firms. The strategic role of BDA was considered not statistically significant in the PLS analysis. This means that despite the clear benefits for decision making, due to its complexity, BDA can sometimes be considered an obstacle for companies. It is not easy to deal with changes created by BDA initiatives. That is also the reason why the path to achieving BDA value is not straightforward.

This led us to conclude that a mixed methodology can be real value to overcome some of Delphi's limitations and reinforces the results of the study. Overall, except for the strategic role of BDA (SR), all the antecedents that derived from Delphi were considered statistically significant to explain BDA sustained value. Our study demonstrates that Delphi can be very powerful to discover antecedents of BDA value. To complement Delphi, quantitative surveys can be quite useful to rearrange the order of the variables and allow for the generalization of the results.

4.1. Academic implications

This research provides several contributions that extend knowledge on BDA in the strategic and planning fields:

(1) **BDA value antecedents** – Even though firms are struggling to achieve BDA benefits (Kaisler, Armour, Espinosa, & Money, 2013),

the path forward remains relatively unknown (Abbasi, Sarker, & Chiang, 2016; Agarwal & Dhar, 2014; Côrte-Real et al., 2017b). This study offers answers to academics by improving knowledge on the antecedents of BDA value. Particular focus was given to the top antecedents that provide sustained business value, and guidelines for implementation were provided based on semi-structured interviews with experts. This study concludes that BDA use is the major contributor to BDA sustained value, followed by the acquisition of dynamic capabilities. It is important to note that firms can attain significant BDA sustained value (R^2 = 62%) by addressing the top strategic BDA challenges.

Nevertheless, in order to obtain more competitive advantages, all of the more operational/innovation related aspects should be tackled as well. Finally, researchers can benefit from this study's results to formulate hypotheses for future studies related to the effects of BDA. Future studies can extend the data sample by assessing cultural variations of BDA sustained value in industries and/or countries to allow data generalization. Also, longitudinal data could be interesting to be used to examine the stability of BDA value in firms. Finally, quantitative research can be performed to assess BDA real value and BDA operational value.

(2) **Delphi literature** – Although this method is widely used and accepted in IS research (Kasi et al., 2008; Keil et al., 2013), and several studies focus on IT impact of using the Delphi method (Paré et al., 2013), BDA researchers have been slow to adopt it. Only one BI study using the Delphi method was found in the literature (e.g. (Yeoh, Koronios, & Gao, 2008)). In addition, several authors encourage the combination of mixed methods (Chiang, 2013; Venkatesh, Thong, & Xu, 2012), in particular combining Delphi with other methods (Rowe & Wright, 2011). This is the first study exploring the value of BDA in firms that apply the Delphi method complemented by quantitative survey and PLS analysis. Future studies could take advantage of this new Delphi variation to assess other IT innovations. Lastly, this study allows other researchers to perform a Delphi study, as the procedures are fully documented.

4.2. Managerial implications

The findings of this study can help managers to understand that the value provided by big data can be realized only by effective management of BDA initiatives. By discovering and discussing strategic, managerial and operational antecedents of BDA value, practitioners can benefit from this study in two ways. First, this study allows us to understand better BDA technologies, their benefits and what antecedents can have the most effect on the BDA strategy of the organization to leverage the business value provided by BDA. Firms that are considering BDA adoption can have an insight into the potential value of these tools and support information to justify BDA investments. This study demonstrates that BDA use in P&O and PSE is the major contributor to leverage BDA initiatives and attain capabilities that will create value for the organization. The results indicate that European firms should invest in the creation of dynamic capabilities to extract the sustained value of BDA. Hence, managers and executives should embed the guidelines provided into their IT strategy.

Second, this study can be used as a guide with best practices to help executives and managers to evaluate BDA initiatives and capabilities in a more systematic way (e.g., benchmarks). Software vendors can have a perception of how European firms are achieving business value from their BDA investments. It can serve as a support to identify and define a robust BDA strategy and priorities activities, guiding managers in their planning and decision-making.

4.3. Limitations and future research

It is appropriate to point out the limitations that can be explored and possibly overcome in future research. Due to the fact that this study is organized in two phases, the limitations can be reported based on each phase:

(1) **Exploratory research** – As can happen with any Delphi-type study, the results are based on a limited number of factors, despite the number of items in the list being consistent with previous studies (Kasi et al., 2008; Keil et al., 2013; Nakatsu & Iacovou, 2009). This study had a positivist orientation, and the factors regarding the negative aspects of BDA in organizations were not addressed. Secondly, although the Delphi panel was small (N = 22), it was methodologically sufficient and consistent with other studies reported in IS literature (Akkermans et al., 2003; Kasi et al., 2008; Keil et al., 2013). Thirdly, this study presents heterogeneous views that can potentially influence the interpretation of the findings. According to Delphi methodology, the sample does not have to be statistically representative (Powell, 2003), but caution is needed when interpreting the BDA framework as well as generalizing it. It is essential to take into consideration that the experts' panel was relatively heterogeneous with a variety of professional experiences in several industry sectors and job positions (as shown in Table 2). Still, we can have some confidence in arguing that, based on a wide coverage of experts' profiles, we have no reason to believe the results are biased. Lastly, although a moderate level of consensus was reached, Kendall's W achieved (0.52) was considered good enough since it is consistent with other Delphi studies in IS literature (Kasi et al., 2008; Nakatsu & Iacovou, 2009; Nevo & Chan, 2007; Schmidt, 1997). Additional rounds could have increased this concordance indicator, but we assumed it would have a smaller participation rate. In the last round, experts were demotivated with the study, as reflected by the considerable number of reminders sent during the process.
(2) **Confirmatory research** – To overcome some of the Delphi limitations, a multi-country survey was conducted. Notwithstanding, some limitations can also be raised in the interpretation of this part of the study. The list of antecedents is not exhaustive, meaning that other factors can also affect the creation of BDA sustained value in European companies. Also, even though the sample is considered statistically reasonable, a larger sample could reinforce the conclusions. The scope of countries could also be extended. As leadership factors can be valued differently in different cultures, it might be useful to perform this study in two different countries and compare the findings. Due to the influence of BDA maturity in the creation of business value, it might be interesting to conduct a longitudinal study.
(3) **Combined research methodology** – Due to survey size restrictions, this study only allows comparison between methods for the variables that contribute to sustained BDA value. Future studies could perform a survey to cross-validate the other types of BDA value.

As the way to extract business value from BDA initiatives is not clear, it is important to provide guidance for academics and practitioners in this matter. Table 7 provides the consolidated view of our results in comparison with previous literature, providing practical guidelines for executives.

5. Conclusion

BDA is vital for firms operating amidst highly competitive environments. This study explored the antecedents of BDA sustained value and its impacts on firm performance. Drawing on the business value of IT, dynamic capabilities, environmental dynamics, IT use, and IT/

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Table 7
Summary of findings and guidelines.

Factor order by Delphi study results	Best practices/strategic guidelines	Survey order of contribution	Previous studies
#1 - dynamic capabilities	Define and plan a strategy to develop dynamic capabilities - Strategies should be supported by business and product strategies and BDA Capability documents. These documents detail how capabilities will be developed. The planned strategies enable the companies to understand the requirements to deliver the product or service, the expected returns on investment and the capabilities and resources required to deliver the strategy.	#3 – statistically significant	(Erevelles et al., 2016; Lin & Wu, 2014; Sher & Lee, 2004; Wamba et al., 2017).
#2 - firm agility	As part of DC, the best practices mentioned above should be considered.	As it is part of DC this variable was not included to avoid redundancy	(Daniel Q. Chen et al., 2016; Côrte-Real et al., 2017a; Tallon & Pinsonneault, 2011).
#3 - strategic alignment between IT and business	1. Assessment - Clearly understand business needs related with big data and desired capabilities. Define a formal team with a moderator role to allow an effective communication between IT and business. 2. Convert requirements into real use cases. Both sides should be able to have a clear view on what, how and when implement each capabilities and integration of data sources.	#4 – statistically significant	(Akter et al., 2016; Tallon & Pinsonneault, 2011).
#4 - BDA strategic role	BDA managers need set up a BDA program correctly. 1. Top management commitment - Select and engage the sponsors - Take advantage from BDA hype to engage the sponsorship. To select the correct sponsors, consider the ones that can set up a list of business goals and a realistic timeline. Gather people from IT and business and convince the sponsors of the impacts of BDA. Running some proof of concept (PoC) can be quite helpful for them to perceive the potential business value. Explain the importance of commitment in order to be able to extract the business value from these initiatives. 2. Define the scope - Based on a well-defined target of business results, you can start to establish a scope in which the supportive technology needs to be installed. 3. Consider a long learning curve - BDA introduces new technologies, techniques, methodologies, and even skills. BDA technologies imply a significant amount of custom development. As there is a serious lack of data scientists, the team will learn as it goes and understand its real value. Therefore, manage stakeholders' expectations and consider some deviations in the program schedule.	Not statistically significant	
#5 - BDA use	1. Communication - Promote the tools within the organization highlighting the benefits of have access to big data (e.g. specific business analysis) but also managing expectations (demonstrations, presentations to top management) 2. Training - Define a training plan in cooperation with business users that already use the tools. Provide training with genuine use cases for the remaining users to understand the value. 3. Feedback/Follow-up - Continuously assess the current usage to discover potential improvements and issues 4. User Experience - To explore big data it is very important to: Use advanced analytics techniques - Text analytics, stream analytics, and advanced analytics (machine learning). For that, it is essential to have data scientists who are knowledgeable on the business and have some IT background. Use BDA to create predictive models and understand behaviors (customer, partners, etc.) Use analytical modelling techniques - Big data does not change the logic of analytical modelling. Small sample size generates big results.	#1 – statistically significant	Wamba et al., 2017; Tallon & Kraemer, 2007; Zhu & Kraemer, 2005).
#6 - environmental volatility	1. Flexibility and constant adaptability in the way BDA applications are developed is key to quickly align with potential environmental changes (internal and external). This should be considered in any BDA initiative. The strategy needs to be adapted according with the market needs (e.g. customer needs, market trends). The strategy is moving target that needs to be realigned to external factors in order to internally grow. 2. Sensing - The environmental volatility can impact on all the top factors, specifically dynamic capabilities. For that reason, constant sensing activities should be carried out by the organization (competitors' analysis, market research studies, surveys…). In addition, organizations should take advantage of their internal knowledge and also ask to internal staff what they suggest to respond to the market challenges.	#2 – statistically significant	(Pavlou & El Sawy, 2011; Tallon & Pinsonneault, 2011).

business alignment literature facilitated the development of research hypotheses and conceptual framework that explicates these relationships. We conducted an empirical study among European firms to test the research model and hypotheses.

We confirmed that BDA use is the key driver for BDA sustained value and found that dynamic capabilities and strategic business/IT alignment also positively contribute to the BDA value. Further, we found that the strategic role of BDA has no significant influence on the BDA sustained value and confirmed the negative influence of environmental volatility on BDA value creation.

This study represents a significant advance in our theoretical understanding of the antecedents of BDA sustained business value. The results also provide instrumental insights for managers to promote BDA use to more effectively extract their value potential. We hope that this work inspires future attempts to elaborate on our findings.

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Appendix A. Survey questionnaire

Constructs	Items	Source
Dynamic capabilities	Please indicate the degree to which the use of BDA tools in the last three years has helped to: DC1. Develop new product or service DC2. Implement new business process DC3. Create new customer relationships DC4. Change way of doing business	(Drnevich & Kriauciunas, 2011)
Strategic alignment between business and IT	For each business process, please consider the critical business activities and identify the extent to which these activities have been implemented by your firm supported by BDA applications. SA1. Supplier relations: forge closer links with suppliers, monitor quality, monitor delivery times, gain leverage over suppliers, negotiate pricing. SA2. Productions and Operations: improve throughput, boost labor productivity, improve flexibility and equipment utilization, streamline operations. SA3. Product and Service Enhancement: embed IT in products, increase pace of development/R&D, monitor design cost, improve quality, support innovation. SA4. Sales and Marketing Support: spot market trends, anticipate customer needs, build market share, improve forecast accuracy, evaluate pricing options. SA5. Customer relations: respond to customer needs, provide after-sales service and support, improve distribution, create customer loyalty.	(Tallon & Pinsonneault, 2011)
Strategic role of BDA	Please indicate the degree to which you agree with the following statements. SR1. BDA is an agent of change, facilitating critical changes to business processes SR2. BDA enables business improvement by being integrated into products and services SR3. BDA facilitates strategic leadership through innovative applications To what extent is BDA used to support critical business activities in each of the following processes?	(Tallon & Kraemer, 2007)
BDA use	To what extent is BDA used to support key business activities in each of the following business processes? USE1. Supplier relations: forge closer links with suppliers, monitor quality, monitor delivery times, gain leverage over suppliers, negotiate pricing. USE2. Production and operations: improve throughput, boost labor productivity, improve flexibility and equipment utilization, streamline operations. USE3. Product and service enhancement: embed IT in products, increase pace of development/R&D, monitor design cost, improve quality, support innovation. USE4. Marketing and sales: spot market trends, anticipate customer needs, build market share, improve forecast accuracy, evaluate pricing options. USE5. Customer relations: respond to customer needs, provide after-sales service and support, improve distribution, create customer loyalty	(Tallon & Kraemer, 2007)
Environmental volatility	Please indicate the degree to which you agree with the following statements. Technological turbulence TT1. Extent of technological turbulence in the environment TT2. Leadership in product/process innovation TT3. Impact of new technology on operations Market turbulence MT1. Extent of market turbulence in the market MT2. Frequent changes in customer preferences MT3. Ability to reduce market uncertainty MT4. Ability to respond to market opportunities	(Menguc & Auh, 2006)
Competitive advantage	Please indicate the degree to which you agree with the following statements. Strategic performance SP1. We have gained strategic advantages over our competitors SP2. We have a large market share. SP3. Overall, we are more successful than our major competitors. Financial performance FP1. Our EBIT (earnings before interest and taxes) is continuously above industry average. FP2. Our ROI (return on investment) is continuously above industry average. FP3. Our ROS (return on sales) is continuously above industry average.	(Schilke, 2014)
Control variables		
Time since BDA adoption	Number of years since adoption (#)	(Elbashir et al., 2013)
Firm size		N/A

Notes: (1) * items eliminated due to low loading. (2) Items were measured using a 7-point numerical scale (1 is strongly disagree and 7 is strongly agree).

References

Abbasi, A., Sarker, S., & Chiang, R. H. (2016). Big data research in information systems: Toward an inclusive research agenda. *Journal of the Association for Information Systems, 17*(2), 3.

Agarwal, R., & Dhar, V. (2014). Editorial—Big data, data science, and analytics: The opportunity and challenge for IS research. *Information Systems Research, 25*(3), 443–448. https://doi.org/10.1287/isre.2014.0546.

Akkermans, H. A., Bogerd, P., Yücesan, E., & van Wassenhove, L. N. (2003). The impact of ERP on supply chain management: Exploratory findings from a European Delphi study. *European Journal of Operational Research, 146*(2), 284–301. https://doi.org/10.1016/s0377-2217(02)00550-7.

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. https://doi.org/10.1016/j.ijpe.2016.08.018.

Barton, D. (2012). Making advanced analytics work for you. *Harvard Business Review, 90*, 78–83.

Bhatt, G. D., & Grover, V. (2014). Types of information technology capabilities and their role in competitive advantage: An empirical study. *Journal of Management Information Systems, 22*(2), 253–277. https://doi.org/10.1080/07421222.2005.11045844.

Brislin, R. W. (1970). Back-translation for cross-cultural research. *Journal of Cross-Cultural Psychology, 1*(3), 185–216. https://doi.org/10.1177/135910457000100301.

Cai, Z., Huang, Q., Liu, H., Davison, R. M., & Liang, L. (2013). *Developing organizational agility through IT capability and KM capability: The moderating effects of organizational climate.* (Paper presented at the PACIS).

Chau, M., & Xu, J. (2012). Business intelligence in blogs: Understanding consumer interactions and communities. *MIS Quarterly, 36*(4), 1189–1216.

Chen, D. Q., Preston, D. S., & Swink, M. (2015). How the use of big data analytics affects value creation in supply chain management. *Journal of Management Information Systems, 32*(4), 4–39.

Chen, D. Q., Preston, D. S., & Swink, M. (2016). How the use of big data analytics affects value creation in supply chain management. *Journal of Management Information Systems, 32*(4), 4–39. https://doi.org/10.1080/07421222.2015.1138364.

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

Chen, Y., Wang, Y., Nevo, S., Jin, J., Wang, L., & Chow, W. S. (2014). IT capability and organizational performance: The roles of business process agility and environmental factors. *European Journal of Information Systems, 23*(3), 326–342.

Chiang, Y.-H. (2013). Using a combined AHP and PLS path modelling on blog site evaluation in Taiwan. *Computers in Human Behavior, 29*(4), 1325–1333. https://doi.org/10.1016/j.chb.2013.01.025.

Chin, W. W. (1998). The partial least squares approach for structural equation modeling. *Modern methods for business research* (pp. 295–336). Mahwah, NJ, US: Lawrence Erlbaum Associates Publishers.

Chuang, S.-H. (2004). A resource-based perspective on knowledge management capability and competitive advantage: An empirical investigation. *Expert Systems with Applications, 27*(3), 459–465.

Côrte-Real, N., Oliveira, T., & Ruivo, P. (2017a). Assessing business value of Big Data Analytics in European firms. *Journal of Business Research, 70*, 379–390.

Côrte-Real, N., Oliveira, T., & Ruivo, P. (2017b). Assessing business value of Big Data Analytics in European firms. *Journal of Business Research*. https://doi.org/10.1016/j.jbusres.2016.08.011.

Dalkey, N., & Helmer, O. (1963). An experimental application of the Delphi method to the use of experts. *Management Science, 9*(3), 458–467.

Daniel, E. M., & White, A. (2005). The future of inter-organisational system linkages: findings of an international Delphi study. *European Journal of Information Systems, 14*(2), 188–203. https://doi.org/10.1057/palgrave.ejis.3000529.

Davenport, T. H., & Dyché, J. (2013). Big data in big companies. *3*, 22–25. Retrieved from https://www.sas.com/en_us/whitepapers/bigdata-bigcompanies-106461.html.

Debecq, A., Van de Ven, A. H., & Gustafson, D. (1975). *Group techniques for program planning.* Glenview, Illinois: Scott, Foresman and Company.

Delen, D., & Zolbanin, H. M. (2018). The analytics paradigm in business research. *Journal of Business Research, 90*, 186–195. https://doi.org/10.1016/j.jbusres.2018.05.013.

DeLeo, W. (2004). Safety educators and practitioners identify the competencies of an occupational safety and environmental health doctoral degree: An on line application of the Delphi technique. *Journal of Safety, Health and Environmental Research, 1*(1), 1–16.

Drnevich, P. L., & Kriauciunas, A. P. (2011). Clarifying the conditions and limits of the contributions of ordinary and dynamic capabilities to relative firm performance. *Strategic Management Journal, 32*(3), 254–279.

Elbashir, M. Z., Collier, P. A., Sutton, S. G., Davern, M. J., & Leech, S. A. (2013). Enhancing the business value of business intelligence: The role of shared knowledge and assimilation. *Journal of Information Systems, 27*(2), 87–105. https://doi.org/10.2308/isys-50563.

Erevelles, S., Fukawa, N., & Swayne, L. (2016). Big data consumer analytics and the transformation of marketing. *Journal of Business Research, 69*(2), 897–904. https://doi.org/10.1016/j.jbusres.2015.07.001.

Fink, L., & Neumann, S. (2009). Exploring the perceived business value of the flexibility enabled by information technology infrastructure. *Information & Management, 46*(2), 90–99.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39–50. https://doi.org/10.2307/3151312.

Fosso Wamba, S., Akter, S., & de Bourmont, M. (2018). Quality dominant logic in big data analytics and firm performance. *Business Process Management Journal*. https://doi.org/10.1108/BPMJ-08-2017-0218.

Fosso Wamba, S., Akter, S., Edwards, A., Chopin, G., & Gnanzou, D. (2015). How 'big data' can make big impact: Findings from a systematic review and a longitudinal case study. *International Journal of Production Economics, 165*, 234–246. https://doi.org/10.1016/j.ijpe.2014.12.031.

Gallego, M. D., Luna, P., & Bueno, S. (2008). Designing a forecasting analysis to understand the diffusion of open source software in the year 2010. *Technological Forecasting and Social Change, 75*(5), 672–686.

Gefen, D., & Straub, D. (2005). A practical guide to factorial validity using PLS-Graph: Tutorial and annotated example. *Communications of the Association for Information systems, 16*(1), 5.

Günther, W. A., Rezazade Mehrizi, M. H., Huysman, M., & Feldberg, F. (2017). Debating big data: A literature review on realizing value from big data. *Journal of Strategic Information Systems, 26*(3), 191–209. https://doi.org/10.1016/j.jsis.2017.07.003.

Gupta, A., Deokar, A., Iyer, L., Sharda, R., & Schrader, D. (2018). Big data & analytics for societal impact: Recent research and trends. *Information Systems Frontiers, 20*(2), 185–194. https://doi.org/10.1007/s10796-018-9846-7.

Habjan, A., Andriopoulos, C., & Gotsi, M. (2014). The role of GPS-enabled information in transforming operational decision making: An exploratory study. *European Journal of Information Systems, 23*(4), 481–502. https://doi.org/10.1057/ejis.2014.2.

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of Marketing Theory and Practice, 19*(2), 139–152.

Hair, J. F., Jr., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2013). *A primer on partial least squares structural equation modeling (PLS-SEM).* Sage Publications.

Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). The use of partial least squares path modeling in international marketing. *Advances in International Marketing, 20*, 277–320.

Hsu, C.-C., & Sandford, B. A. (2007). The Delphi technique: Making sense of consensus. *Practical Assessment, Research & Evaluation, 12*(10), 1–8.

Işık, Ö., Jones, M. C., & Sidorova, A. (2013). Business intelligence success: The roles of BI capabilities and decision environments. *Information & Management, 50*(1), 13–23. https://doi.org/10.1016/j.im.2012.12.001.

Jeble, S., Dubey, R., Childe, S. J., Papadopoulos, T., Roubaud, D., & Prakash, A. (2018). Impact of big data and predictive analytics capability on supply chain sustainability. *International Journal of Logistics Management, 29*(2), 513–538.

Kaisler, S., Armour, F., Espinosa, J. A., & Money, W. (2013). *Big data: Issues and challenges moving forward.* (Paper presented at the System Sciences (HICSS), 2013 46th Hawaii International Conference on System Sciences).

Kasi, V., Keil, M., Mathiassen, L., & Pedersen, K. (2008). The post mortem paradox: A Delphi study of IT specialist perceptions. *European Journal of Information Systems, 17*(1), 62–78.

Keil, M., Lee, H. K., & Deng, T. (2013). Understanding the most critical skills for managing IT projects: A Delphi study of IT project managers. *Information & Management, 50*(7), 398–414.

Kiron, D., & Shockley, R. (2011). Creating business value with analytics. *MIT Sloan Management Review, 53*(1), 56–63.

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. https://doi.org/10.1016/j.ijinfomgt.2014.02.002.

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), 21–31.

Lin, Y., & Wu, L.-Y. (2014). Exploring the role of dynamic capabilities in firm performance under the resource-based view framework. *Journal of Business Research, 67*(3), 407–413.

Linstone, H. A., & Turoff, M. (1975). *The Delphi method: Techniques and applications. Vol. 29*. Reading, MA: Addison-Wesley.

Loebbecke, C., & Picot, A. (2015). Reflections on societal and business model transformation arising from digitization and big data analytics: A research agenda. *The Journal of Strategic Information Systems, 24*(3), 149–157. https://doi.org/10.1016/j.jsis.2015.08.002.

Marr, B. (2017). How is big data used in practice? 10 uses cases everyone must read. Retrieved from https://www.ap-institute.com/big-data-articles/how-is-big-data-used-in-practice-10-use-cases-everyone-should-read.

Martins, R., Oliveira, T., & Thomas, M. A. (2016). An empirical analysis to assess the determinants of SaaS diffusion in firms. *Computers in Human Behavior, 62*(Supplement C), 19–33. https://doi.org/10.1016/j.chb.2016.03.049.

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.

Menguc, B., & Auh, S. (2006). Creating a firm-level dynamic capability through capitalizing on market orientation and innovativeness. *Journal of the Academy of Marketing Science, 34*(1), 63–73.

Mithas, S., Lee, M. R., Earley, S., Murugesan, S., & Djavanshir, R. (2013). Leveraging big data and business analytics [guest editors' introduction]. *IT Professional Magazine, 15*(6), 18–20. https://doi.org/10.1109/MITP.2013.95.

Moore, G. C., & Benbasat, I. (1991). Development of an instrument to measure the perceptions of adopting an information technology innovation. *Information Systems Research, 2*(3), 192–222. https://doi.org/10.1287/isre.2.3.192.

Nakatsu, R. T., & Iacovou, C. L. (2009). A comparative study of important risk factors involved in offshore and domestic outsourcing of software development projects: A two-panel Delphi study. *Information & Management, 46*(1), 57–68.

Nevo, D., & Chan, Y. E. (2007). A Delphi study of knowledge management systems: Scope and requirements. *Information & Management, 44*(6), 583–597.

Okoli, C., & Pawlowski, S. D. (2004). The Delphi method as a research tool: An example, design considerations and applications. *Information & Management, 42*(1), 15–29. https://doi.org/10.1016/j.im.2003.11.002.

Oliveira, M. P. V.d., McCormack, K., & Trkman, P. (2012). Business analytics in supply chains – The contingent effect of business process maturity. *Expert Systems with Applications, 39*(5), 5488–5498. https://doi.org/10.1016/j.eswa.2011.11.073.

Paré, G., Cameron, A.-F., Poba-Nzaou, P., & Templier, M. (2013). A systematic assessment of rigor in information systems ranking-type Delphi studies. *Information & Management, 50*(5), 207–217.

Pavlou, P. A., & El Sawy, O. A. (2011). Understanding the elusive black box of dynamic capabilities. *Decision Sciences, 42*(1), 239–273. https://doi.org/10.1111/j.1540-5915.2010.00287.x.

Picoto, W. N., Bélanger, F., & Palma-dos-Reis, A. (2014). An organizational perspective on m-business: Usage factors and value determination. *European Journal of Information Systems, 23*(5), 571–592.

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.

Popovič, A., Hackney, R., Coelho, P. S., & Jaklič, J. (2012). Towards business intelligence systems success: Effects of maturity and culture on analytical decision making. *Decision Support Systems, 54*(1), 729–739. https://doi.org/10.1016/j.dss.2012.08.017.

Popovič, A., Hackney, R., Tassabehji, R., & Castelli, M. (2016). The impact of big data analytics on firms' high value business performance. *Information Systems Frontiers*. https://doi.org/10.1007/s10796-016-9720-4.

Powell, C. (2003). The Delphi technique: Myths and realities. *Journal of Advanced Nursing, 41*(4), 376–382.

Rowe, G., & Wright, G. (2011). The Delphi technique: Past, present, and future prospects - Introduction to the special issue. *Technological Forecasting and Social Change, 78*(9), 1487–1490. https://doi.org/10.1016/j.techfore.2011.09.002.

Ryans, A. B. (1974). Estimating consumer preferences for a new durable brand in an established product class. *Journal of Marketing Research, 11*(4), 434–443. https://doi.org/10.2307/3151290.

Schilke, O. (2014). On the contingent value of dynamic capabilities for competitive advantage: The nonlinear moderating effect of environmental dynamism. *Strategic Management Journal, 35*(2), 179–203.

Schmidt, R. C. (1997). Managing Delphi surveys using nonparametric statistical techniques. *Decision Sciences, 28*(3), 763–774. https://doi.org/10.1111/j.1540-5915.1997.tb01330.x.

Sher, P. J., & Lee, V. C. (2004). Information technology as a facilitator for enhancing dynamic capabilities through knowledge management. *Information & Management, 41*(8), 933–945. https://doi.org/10.1016/j.im.2003.06.004.

Shollo, A., & Galliers, R. D. (2016). Towards an understanding of the role of business intelligence systems in organisational knowing. *Information Systems Journal, 26*(4), 339–367. https://doi.org/10.1111/isj.12071.

Sivarajah, U., Kamal, M. M., Irani, Z., & Weerakkody, V. (2017). Critical analysis of Big Data challenges and analytical methods. *Journal of Business Research, 70*, 263–286. https://doi.org/10.1016/j.jbusres.2016.08.001.

Skulmoski, G., Hartman, F., & Krahn, J. (2007). The Delphi method for graduate research. *Journal of Information Technology Education, 6*(1), 1–21.

Slater, S. F., & Narver, J. C. (2000). Intelligence generation and superior customer value. *Journal of the Academy of Marketing Science, 28*(1), 120. https://doi.org/10.1177/0092070300281011.

Stedman, C. (2013). Analytical models in big data environments often best left small. Retrieved from http://searchbusinessanalytics.techtarget.com/feature/Analytical-models-in-big-data-environments-often-best-left-small.

Tallon, P. P., & Kraemer, K. L. (2007). Fact or fiction? A sensemaking perspective on the reality behind executives' perceptions of IT business value. *Journal of Management Information Systems, 24*(1), 13–54.

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).

Toonen, A., Kanthadai, S., & Jones, S. (2016). The big data payoff: Turning big data into business value. Retrieved from https://www.capgemini.com/resource-file-access/resource/pdf/the_big_data_payoff_turning_big_data_into_business_value.pdf.

Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly, 36*(1), 157–178.

Verhoef, P. C., Kooge, E., & Walk, N. (2016). *Creating value with big data analytics: Making smarter marketing decisions.* Routledge.

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. https://doi.org/10.1016/j.jbusres.2016.08.009.

White, S. (2015). Study reveals that most companies are failing at big data.CIO.com. Retrieved from http://www.cio.com/article/3003538/big-data/study-reveals-that-most-companies-are-failing-at-big-data.html.

Yeoh, W., Koronios, A., & Gao, J. (2008). Managing the Implementation of Business Intelligence Systems. *International Journal of Enterprise Information Systems, 4*(3), 79–94. https://doi.org/10.4018/jeis.2008070106.

Zhu, K., & Kraemer, K. L. (2005). Post-adoption variations in usage and value of e-business by organizations: Cross-country evidence from the retail industry. *Information Systems Research, 16*(1), 61–84. https://doi.org/10.1287/isre.1050.0045.

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