Journal of Business Research 70 (2017) 379–390

Contents lists available at ScienceDirect

Journal of Business Research

# Assessing business value of Big Data Analytics in European firms☆

Nadine Côrte-Real *, Tiago Oliveira, Pedro Ruivo

*NOVA IMS, Universidade Nova de Lisboa, 1070-312, Lisboa, Portugal*

ARTICLE INFO

Available online 9 August 2016

*Keywords:*
Big Data Analytics (BDA)
IT business value
Knowledge Based View (KBV)
Dynamic capabilities (DC)
Organizational agility
Competitive advantage

ABSTRACT

In the strategic management field, dynamic capabilities (DC) such as organizational agility are considered to be paramount in the search for competitive advantage. Recent research claims that IT business value research needs a more dynamic perspective. In particular, the Big Data Analytics (BDA) value chain remains unexplored. To assess BDA value, a conceptual model is proposed based on a knowledge-based view and DC theories. To empirically test this model, the study addresses a survey to a wide range of 500 European firms and their IT and business executives. Results show that BDA can provide business value to several stages of the value chain. BDA can create organizational agility through knowledge management and its impact on process and competitive advantage. Also, this paper demonstrates that agility can partially mediate the effect between knowledge assets and performance (process level and competitive advantage). The model explains 77.8% of the variation in competitive advantage. The current paper also presents theoretical and practical implications of this study, and the study's limitations.



## 1. Introduction

In the era of Big Data, firms in every sector are required to deal with a huge amount of data. Data in vast amounts can offer invaluable insights and competitive advantage if the right technological and organizational resources support them (Morabito, 2015). Recently, several academics and practitioners have stressed the need to understand how, why, and when Big Data Analytics (BDA) applications can be a valuable resource for companies to gain competitive advantage (Abbasi, Sarker, & Chiang, 2016; Agarwal & Dhar, 2014; Corte Real, Oliveira, & Ruivo, 2014; LaValle et al., 2011). Although BDA technologies have been recognized as the "next big thing for innovation" (i.e., a potential source of business value and competitive advantage), the BDA value chain remains relatively unexplored and needs further investigation. No empirical research exists assessing how BDA can bring business value (Abbasi et al., 2016), establishing a linkage between knowledge assets, organizational agility, and performance (process-level and competitive advantage) (Corte Real et al., 2014). Firms that inject BDA in their business operations can surpass their peers by 5% in productivity and 6% in profitability (Barton, 2012). For that reason, European firms are investing heavily in BDA technologies (SAS, 2013; Sharma, Mithas, & Kankanhalli, 2014). Nevertheless, this investment can only be valuable if organizations use the appropriate technology and organizational resources to achieve competitive advantage (Manyika et al., 2011a).

In response to the scarcity of research on this subject, this study examines the impact of BDA on the business value chain in a European context by empirically testing a new theoretical framework that merges two strategic management theories (Knowledge Based View (KBV) and dynamic capabilities (DC)) at firm-level. Not only does this paper extend BDA research by transposing, merging, and examining hypotheses in IT innovations and management fields, but also contributes to DC research by empirically assessing the antecedents and impacts of a specific dynamic capability (organizational agility), when using BDA technologies. This is the first paper that studies the entire BDA value chain at firm-level, linking concepts of knowledge management, agility, and performance (process-level and competitive advantage). To clarify the role of agility on performance, this papers tests if agility is a mediator of knowledge assets on performance (process-level performance and competitive advantage). The study explores the following three research questions (RQs):

RQ1 – What are the BDA enablers for the creation of organizational agility?
RQ2 – What are the impacts of this dynamic capability created by BDA on sustainable competitive advantage?
RQ3 – Is agility a mediator of knowledge assets on performance (process-level performance and competitive advantage)?

☆ The author is grateful for the comments by anonymous reviewers, on earlier drafts of this article.

* Corresponding author.
*E-mail address:* nreal@novaims.unl.pt (N. Côrte-Real).

http://dx.doi.org/10.1016/j.jbusres.2016.08.011
0148-2963/

This study offers guidance for executives and managers to assess the conditions under which BDA can add business value to organizations. Managers and IT executives can benefit from an evaluation instrument to assess the impact of BDA. Also, this paper provides valuable support to justify BDA investments and initiatives. Firms that have not yet decided to adopt these technologies can obtain a view of potential gains from adopting and effectively using BDA. This research demonstrates how best to leverage the knowledge embedded in BDA systems, acquiring organizational agility capabilities that lead toward competitive advantage.

The remainder of this paper has the following structure: Section 2 provides an introduction to the BDA concept and a theoretical background to assess BDA initiatives; Section 3 presents the conceptual model and the hypotheses; Section 4 outlines the methodology; and Section 5 shows the empirical results. Finally, the paper presents a discussion and the conclusions from the findings.

## 2. Background

### 2.1. Big Data Analytics

Chen, Chiang (Chen, Chiang, & Storey, 2012) coined the term Big Data Analytics (BDA) as a related field of business intelligence & analytics (BI&A), referring to the BI&A technologies that mostly concern data mining and statistical analysis. Authors define BDA as "*a new generation of technologies and architectures, designed to economically extract value from very large volumes of a wide variety of data, by enabling high velocity capture, discovery and/or analysis.*" (IDC, 2011). BDA technologies allow firms to improve existing applications by offering business-centric practices and methodologies that provide a competitive advantage (Chen et al., 2012; Davenport, 2006). The latest literature indicates that there is much room for further BDA research (Abbasi et al., 2016; Agarwal & Dhar, 2014; Erevelles, Fukawa, & Swayne, 2016). There are already academic studies that reflect the adoption and use of BDA (e.g., (Malladi, 2013; Xu, Frankwick, & Ramirez, 2016; Kwon, Lee, & Shin, 2014)). Regarding value, most BDA academic studies focus on analyzing business value from a data or system perspective (e.g., (LaValle et al., 2011; Kwon et al., 2014)). From the strategic management perspective only one conceptual paper explores how BDA affects several marketing activities (Erevelles et al., 2016). The remaining literature addresses industry primarily (LaValle et al., 2011; Russom, 2011). As firms do not know how to capture business value (Barton, 2012; LaValle et al., 2011), some scholars (Corte Real et al., 2014; Malladi, 2013) argue that BDA value research is scarce and needs to extend beyond post-adoption stages toward competitiveness (Erevelles et al., 2016; Xu et al., 2016). Although numerous approaches assess IT Value at the process and firm levels (see Schryen (Schryen, 2013) for a review), this study extends IT business value research from the strategic management perspective, by empirically assessing the BDA business value chain in European firms.

### 2.2. Theoretical foundation

Many studies in recent decades investigate IT business value and competitive advantage using the resource-based view (RBV) (Barua, Kriebel, & Mukhopadhyay, 1995; Bharadwaj, 2000; Mata, Fuerst, & Barney, 1995; Melville, Kraemer, & Gurbaxani, 2004; Ruivo, Oliveira, & Neto, 2015; Soh & Markus, 1995; Zhu & Kraemer, 2005). The limitations of RBV encourage the use of other theories such as DC and KBV (Arend & Bromiley, 2009; Wang & Ahmed, 2007). As DC theory constitutes the second foundation that supports knowledge-based thinking (Pettigrew, Thomas, & Whittington, 2001), this study combines these theories. KBV explores a firm's potential to acquire competitiveness in a dynamic market context, but only DC theory can solve the problem of sustaining competitive advantage in turbulent environments (Grant, 1996; Volberda, 1996).

#### 2.2.1. Knowledge Based View theory

KBV states that a firm's knowledge resources are unique and inimitable and that the firm's primary function is to leverage them into productive outcomes (Grant, 1996; Nonaka, 1995). The possession of knowledge resources gives the firm basic foundations to renew or reconfigure its resource base and to build dynamic capabilities (Wu, 2006), such as organizational agility. Companies that have high levels of staff knowledge and involvement can more skillfully identify the need to make changes to existing resources and decide about the actions necessary to implement these changes (Nieves & Haller, 2014). KBV theory can help to conceptualize the performance effects of IT investments (Pavlou et al., 2005). Management studies use this theory (e.g., (Nieves & Haller, 2014)), as do studies in IT fields (e.g., (Sher & Lee, 2004)) to understand the role of knowledge management in the creation of DC. In BDA technologies, Xu, Frankwick (Xu et al., 2016) seek to understand the relationships among traditional marketing analytics, BDA, and new product success. The current paper is the first that empirically tests KBV to understand the role of BDA in the creation of agility.

#### 2.2.2. Dynamic capability theory

In the past decade the DC perspective arose as one of the most effective theoretical lenses for the strategic management field (Schilke, 2014), attracting the interest of scholars not only in business, but also in the IT management field (Helfat et al., 2009; Protogerou, Caloghirou, & Lioukas, 2012). Rooted in RBV and KBV, DC argues that the dynamic capabilities enable firms to modify their resource to adapt rapidly to changing conditions, helping them to sustain their competitive advantage over time (Helfat & Peteraf, 2009; Teece, Pisano, & Shuen, 1997). Although the literature has a broad range of definitions for DC, one of the seminal papers defines DC as "*the ability to integrate, build, and reconfigure internal and external competencies to address rapidly-changing environments*" (Teece et al., 1997). DC disaggregates into "the capacity (1) to sense and shape opportunities and threats, (2) to seize opportunities, and (3) to maintain competitiveness through enhancing, combining, protecting, and, when necessary, reconfiguring the business enterprise's intangible and tangible assets".

Some authors argue that agility is an organizational dynamic capability (Blome, Schoenherr, & Rexhausen, 2013; Sambamurthy et al., 2007; Zhou & Wu, 2010). Teece (Teece, 2007) defines agility as a higher-order dynamic capability that emerges over time, generally defining agility as a capability with which firms can identify and respond to environmental threats and opportunities and quickly adjust their behaviors (Goldman, Nagel, & Preiss, 1995; Sambamurthy, Bharadwaj, & Grover, 2003). This concept also relates to the operational flexibility of organizational processes and IT systems to support structured or unstructured changes (Chen et al., 2014). Achieving agility demands processing a large and varied amount of information (Goldman et al., 1995). This process is possible with BDA applications. However, like IT applications (Sambamurthy et al., 2003; Weill, Subramani, & Broadbent, 2002), BDA tools cannot automatically improve agility. In fact, under certain conditions BDA tools can impede agility (Chen et al., 2014). For this reason, the need exists to understand how BDA applications can create agility.

Several recent studies in the business management field apply DC theory to measure the influence of DC in the creation of competitive advantages (e.g., Schilke, 2014; Zott, 2003; Drnevich & Kriauciunas, 2011). In the IT management field, few empirical studies use this theory. Analyzing the IT influence on DC generically, (Chen et al., 2014; Sher & Lee, 2004), researchers conclude that IT is an enabler of DC in organizations. Regarding agility, several studies assess the impact of IT on organizational agility (e.g., Sambamurthy et al., 2007; Chen et al., 2014; Cai et al., 2013; Tallon & Pinsonneault, 2011; Liu et al., 2013; Lu & Ramamurthy, 2011). These studies demonstrate a positive relationship between IT and agility. Chen (Chen et al., 2014) recently concludes that the IT business value essentially depends on how agile a firm is with regard to managing business processes. Although the literature addresses the impact of IT on the creation of organizational agility, no study links BDA with this specific DC. Apart from some qualitative studies in the area of business analytics (BA) (Shanks & Bekmamedova, 2013; Shanks & Sharma, 2011), only conceptual papers use DC theory to study BDA value (Corte Real et al., 2014; Erevelles et al., 2016).

Firms that do not develop the resources and capabilities to use BDA applications will struggle to develop a sustainable competitive advantage (Erevelles et al., 2016). Given that agility is vital for companies´ survival, and that BDA can support organizational business processes, this study fills this academic gap and links the two concepts empirically.

## 3. Conceptual model

With recourse to the two strategic management theories (KBV and DC) discussed above, this section explains the conceptual model and the specific hypotheses (Fig. 1).

Rooted in an earlier conceptual model (Corte Real et al., 2014), this research model empirically tests 12 propositions. The study assesses the entire value chain starting with how BDA can leverage different forms of knowledge to create organizational agility (H1, H2, H3). BDA technologies can provide organizational agility to the firm by using effective knowledge management. Firms owning this type of dynamic capability can achieve competitive advantage directly (H4a) or indirectly through business processes (H4b). Results obtained by using business processes will impact the overall organization (H5). Agility can also mediate the relationship between knowledge assets and performance (H6a,b,c-H7a,b,c). BDA uses some controls such as country, industry, technological turbulence, and time.

### 3.1. Hypothesis

#### 3.1.1. Knowledge assets

Organizational knowledge such as operational routines, skills, and know-how constitutes a key source of competitiveness (Grant, 1996). Knowledge management plays a critical role in proficiently managing data and delivering it to the end users to support business processes (Rajpathak & Narsingpurkar, 2013). Knowledge management represents a dimension supported by KBV (Ruggles, 1998) and enables dynamic capabilities by offering specific functional competences that can improve business performance (Teece et al., 1997). A natural relationship exists between KM and BDA. Both deal with intangible assets such as data, knowledge, and intelligence (Erickson & Rothberg, 2015). BDA is a source of knowledge management, allowing firms to add value primarily at the beginning of the information value chain and helping knowledge to flow to achieve business excellence (Chau & Xu, 2012; Popovič et al., 2012).

Big data is a potential knowledge asset, contingent upon the proper use of that knowledge (Erickson & Rothberg, 2015). BDA represents technologies drivers of a strategic knowledge asset (big data). BDA applications have the potential to add value by providing more transparent and accurate results to support decision-making in several business areas (Manyika et al., 2011a).

BDA strategy requires the capacity to sense, acquire, process, store, and analyze the data and convert that data into knowledge (Rajpathak & Narsingpurkar, 2013). Several empirical studies state that the knowledge processes are antecedent dimensions of successful DC, by allowing firms to continually renew their knowledge base and deliver business performance (Ambrosini & Bowman, 2009; Sher & Lee, 2004; Zheng, Zhang, & Du, 2011). As DC are information-intensive (Pavlou & El Sawy, 2011), BDA may help in the creation of DC and organizational agility specifically. Using BDA technologies helps to store and share knowledge, thereby allowing for an improvement of organizational knowledge by promoting efficiency within an organization, particularly by data integration and the use of analytical tools (Russom, 2011). Some authors argue that firms must combine endogenous and exogenous knowledge to achieve DC (Sher & Lee, 2004). Zhao (Cai et al., 2013) argues that IT capability and KM capability are important in fostering organizational agility. Agility is promoted through knowledge management by improving innovative responses, and can improve through the use of IT and automated business processes (Cai et al., 2013). In the same way, organizations should be able to use BDA technologies to convert knowledge into new routines and enhance organizational agility. Based on these findings, the hypotheses are:

**H1.** BDA technologies allow an effective endogenous knowledge management that positively influences dynamic capabilities such as organizational agility.

**H2.** BDA technologies allow an effective exogenous knowledge management that positively influences dynamic capabilities such as organizational agility.

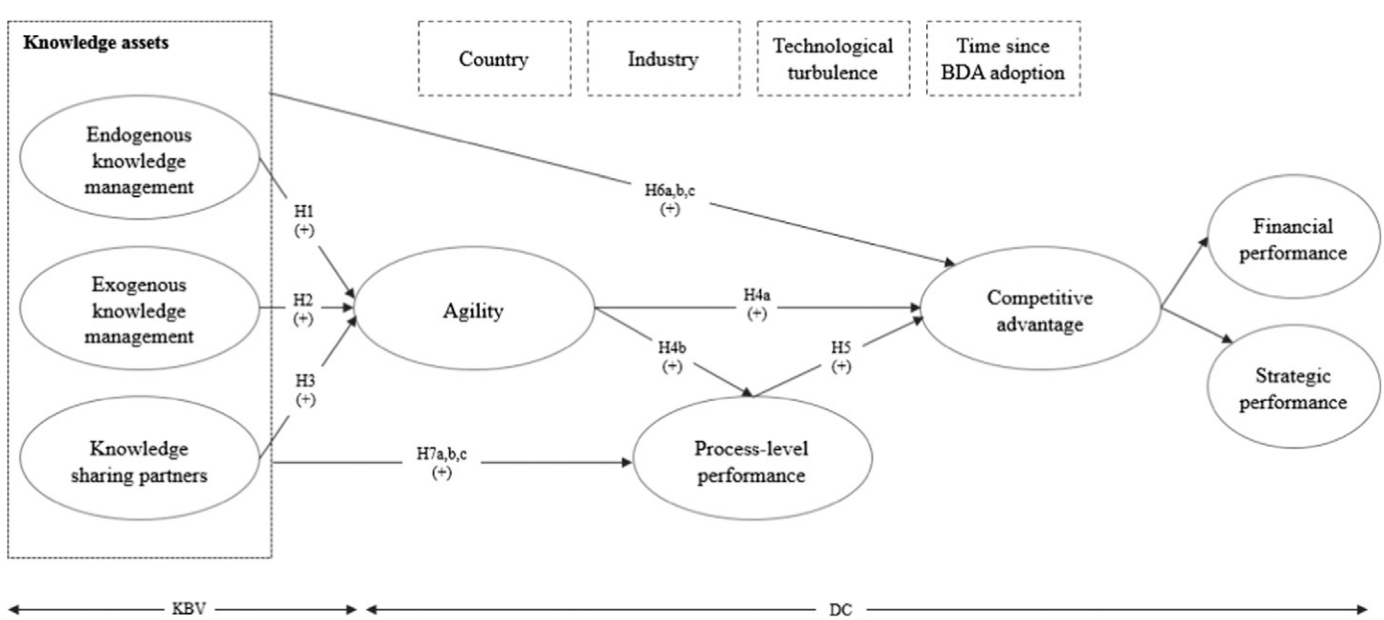


**Fig. 1.** Proposed conceptual model.

Knowledge sharing with key channel partners refers to the extent to which a firm shares insights and know-how about its business context with its partners (Saraf, Langdon, & Gosain, 2007). Channel partners are considered to be tactically and strategically important for companies. They can help to collect crucial market-related information with which to fine tune the strategy to meet customer needs, resulting in long-term financial performance (Lorenzoni & Lipparini, 1999). Literature points out that the collaborative knowledge sharing capacity provides an opportunity to increase value (e.g.,(Saraf et al., 2007)) and enable DC (e.g., (Della Corte & Del Gaudio, 2012)). Considering that DC theory encompasses several levels of analysis, it is important to consider the relational view, including the ability to collaborate with channel partners (Teece, 2007). Literature shows that agility needs the support of effective knowledge sharing (Liu, Song, & Cai, 2014). Some studies link the knowledge sharing capability through IT with agility (e.g., (Cai et al., 2013; Liu et al., 2014)). Such interactions can also benefit from the use of BDA technologies, consequently enhancing organizational agility by influencing the capabilities to sense opportunities and threats, shape them, and seize them (Della Corte & Del Gaudio, 2012). Therefore, another hypothesis is:

**H3.** BDA technologies allow an effective knowledge sharing with partners that positively influences organizational dynamic capabilities such as organizational agility.

*3.1.2. Organizational agility*

DC can play a key role in determining a firm's competitive advantage (Teece et al., 1997; Zott, 2003). Agility is the “capacity of an organization to efficiently and effectively redeploy/redirect its resources to value creating and value protecting (and capturing) higher-yield activities as internal and external circumstances warrant” (Teece, Peteraf, & Leih, 2016). In the management field several researchers recognize that DC does not lead directly to sustainable competitiveness, and that this value derives from improved business processes (e.g., (Schilke, 2014; Drnevich & Kriauciunas, 2011)). Some authors conclude that agility can influence organizational performance (Cai et al., 2013; Liu et al., 2013; Tallon & Pinsonneault, 2011). Hence, additional hypotheses are:

**H4a.** Organizational agility is a dynamic capability leveraged by BDA that positively affects the creation of competitive advantages.

**H4b.** Organizational agility is a dynamic capability leveraged by BDA that positively influences the process-level performance.

By engaging the business activities (e.g., sense customer needs, market research, R&D) companies can increase the possibility of achieving process innovation success (Zollo & Winter, 2002). In the IT field some authors focus on the importance of assessing how business processes can bring value to firms (e.g., (Chen et al., 2014; Tallon, 2007)). Recent conceptual considerations are that BDA is a source of DC (organizational agility, specifically) and that BDA are a way to provide business value to firms (Erevelles et al., 2016). Therefore, the hypothesis is:

**H5.** Process-level performance has a positive effect on competitive advantage.

*3.1.3. The mediating role of agility on the relationship between knowledge assets and performance*

Earlier IT literature considers that dynamic capabilities can establish a link between knowledge assets and firm performance (Sher & Lee, 2004; Wang, Klein, & Jiang, 2007). In the management field some authors examine agility as a mediator between the management of knowledge assets and performance (Chung, 2010; Liu et al., 2014). Also, the proposed model suggests a potential mediating role of agility in the relationship between knowledge assets and two types of performance (process-level performance and competitive advantage). Thus, additional hypotheses are:

**H6a.** Agility positively mediates the relationship between endogenous knowledge management and competitive advantage.

**H6b.** Agility positively mediates the relationship between exogenous knowledge management and competitive advantage.

**H6c.** Agility positively mediates the relationship between knowledge sharing with partners and competitive advantage.

**H7a.** Agility positively mediates the relationship between endogenous knowledge management and process-level performance.

**H7b.** Agility positively mediates the relationship between exogenous knowledge management and process-level performance.

**H7c.** Agility positively mediates the relationship between knowledge sharing with partners and process-level performance.

*3.1.4. Competitive advantage*

Competitive advantage exists when a firm reveals having greater success compared with its current or potential competitors (Peteraf & Barney, 2003). To be consistent with this conceptualization, superior firm performance relative to that of competitors constitutes an empirical and common indicator of competitive advantage. (Barnett, Greve, & Park, 1994; Schilke, 2014). Based on Schilke's construct (Schilke, 2014), competitive advantage was operationalized as reflective-reflective type (Ringle, Sarstedt, & Straub, 2012), with the first-order dimensions of: (1) strategic performance (qualitative dimension) and (2) financial performance (quantitative dimension), both in comparison to competition.

*3.1.5. Controls*

As literature widely supports, this study uses the industry and the country in which a firm competes as predictors of competitiveness (Schilke, 2014). BDA may be particularly useful to firms operating in turbulent technological environments (Wade & Hulland, 2004), and consequently, following the approach of Menguc and Auh (Menguc & Auh, 2006) and Drnevich and Kriauciunas (Drnevich & Kriauciunas, 2011), the study includes turbulent technological environment as a control. A turbulent technological environment makes current technology obsolete and requires the development of new advances (Menguc & Auh, 2006). Finally, we use the variable “time since adoption of BDA” to control for the knowledge and experience that organizations gain by using BDA over time (Elbashir et al., 2013). These controls explain all dependent variables (agility, process-level performance, and competitive advantage).

## 4. Research design

*4.1. Measurement*

To test the model (Fig. 1) and the related hypotheses, the study performs a multi-country survey of European organizations from several industries. Following the recommendations of Moore and Benbasat (Moore & Benbasat, 1991), the study uses a survey instrument drawing upon a comprehensive literature review. Regarding content validity, five established academic IS researchers and two language experts review each item on the questionnaire, assessing its content, scope, and purpose (Brislin, 1970). To test the difficulty of the questions, together with the reliability and validity of the scales, a pilot study uses a sample of 30 executives from firms not part of the main survey. Removal of some items reduces ambiguity and simplifies interpretation. The survey instrument and measurement items are in Appendix A.

### 4.2. Data

The survey was conducted in 2015 using an online survey tool. To guarantee the quality of the data, the respondent profile uses the following three criteria: deep knowledge of the organization strategy, more than five years of experience in BI&A/BDA initiatives, and holding an IT/business executive or management position in the company. The mailing database comes from Dun & Bradstreet, one of the world's leading firms for commercial information and business insight. The initial sample of 500 firm executives from European firms receives an email to participate in the survey.

Ninety-two valid responses were received in the first month. To increase the response rate a follow-up email was sent. During the following months 83 additional valid responses were received from late responders, totaling 175 usable responses (overall response rate of 35%). As seen in Table 1, the sample comprises different industries of which almost half are financial firms (40.5%). Regarding firm size, the sample is equally distributed between mid-size and large companies. Business (41.4%) and IT executives (58.6%) are well represented. Non-response bias was assessed using the sample distributions of the early and late respondent groups compared with the Kolmogorov-Smirnov test (Ryans, 1974) (see Table 2). The early respondents were identified by selecting the respondents in the first month. The test shows that the two groups do not differ statistically (5% significance level, $p > 0.05$), demonstrating the absence of non-response bias (Ryans, 1974). Due to the fact that the study collects data simultaneously from a single source, for the sake of validity, common method bias needs to be assessed. The study uses Harman's post hoc single-factor analysis for this purpose. A factorial analysis of all indicators was conducted and the first extracted factors explain 36.9% of variance. This means that common method bias is unlikely to be an issue in the data Podsakoff et al., 2003.

## 5. Results

To estimate the conceptual model, the study uses the partial least squares (PLS) method (Hair, Ringle, & Sarstedt, 2011). PLS fulfills the research purpose by examining the validity of the constructs, without requiring normal distributions for the variables. PLS requires a sample size of ten times the number of the largest number of structural paths directed at a particular construct (Gefen & Straub, 2005). In the conceptual model the largest number of structural paths directed to a particular construct is three, which means that the minimum sample size should be 30. The sample is larger ($n = 175$), meaning that it is adequate for PLS. Before testing the structural model, the study analyzes the measurement model in order to assess reliability and validity.

**Table 1**
Sample profile.

| Sample characteristics (n = 175) | Obs. | (%) |
|---|---|---|
| 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% |
| Industry | | |
| Manufacturing | 23 | 13.1% |
| Electricity, gas and water supply activities | 11 | 6.2% |
| Wholesale and retail trade | 19 | 10.8% |
| Transports and telecommunications | 18 | 10.2% |
| Financial intermediation | 71 | 40.5% |
| Others | 33 | 18.8% |

Notes: (1) The firm size is categorised based on European enterprises size classification [104]; (2) The industries of activity are in accordance with NACE (European standard classification of productive economic activities).

**Table 2**
Testing possible response bias: early vs. late respondents.

| Constructs | Full sample N = 175 | | Early respondents N = 92 | | Late respondents N = 83 | | Kolmogorov-Smirnov test |
|---|---|---|---|---|---|---|---|
| | Mean | S.D. | Mean | S.D. | Mean | S.D. | p-Value |
| ENKM | 5.9 | 0.71 | 5.9 | 0.67 | 5.9 | 0.75 | 0.65 |
| EXKM | 5.8 | 0.86 | 5.9 | 0.85 | 5.7 | 0.86 | 0.07 |
| KSP | 4.8 | 0.89 | 4.8 | 0.80 | 4.7 | 0.98 | 0.30 |
| AG | 6.1 | 0.93 | 6.1 | 0.78 | 6.0 | 1.07 | 0.72 |
| PLP | 6.1 | 0.81 | 6.1 | 0.78 | 6.0 | 0.83 | 0.23 |
| CA | 5.9 | 0.82 | 6.0 | 0.72 | 5.8 | 0.92 | 0.34 |
| SP | 6.0 | 0.81 | 6.0 | 0.72 | 6.0 | 0.89 | 0.76 |
| FP | 5.9 | 0.96 | 6.0 | 0.81 | 5.7 | 1.09 | 0.16 |

### 5.1. Measurement model

The study examines indicator reliability, construct reliability, convergent validity, and discriminant validity in order to assess the measurement model. Tables 3 and 4 show the results of the measurement model. Regarding indicator reliability, only loadings above 0.7 were considered. Hence, four items (ENKM5, DC1, PLP3-4) were eliminated. As Table 3 reveals, the instrument presents good indicator reliability, as the loadings are above 0.70. The composite reliability coefficient assesses the construct reliability because construct reliability takes into consideration indicators having different loadings (Hair et al., 2011; Henseler, Ringle, & Sinkovics, 2009). Table 4 shows that all constructs have composite reliability above 0.7, which suggests that the constructs are reliable. To test convergent validity, the study uses average variance extracted (AVE). The AVE should be higher than 0.5, (i.e., the latent variable explains more than half of the variance of its indicators (Henseler et al., 2009; Fornell & Larcker, 1981)). Table 4 shows that all constructs meet this criterion. Regarding discriminant validity, the study uses two measures: the Fornell-Larcker criterion and cross-loadings. First, according to Fornell and Larcker (Fornell & Larcker, 1981), the square root of AVE should be greater than the correlations with other latent variables. Table 4 shows that the square roots of AVEs (in bold) are higher than the correlation between constructs. All the constructs show evidence of acceptable discrimination. Second, the loading of each indicator should be greater than all cross-loadings (Chin, 1998a) (see Table 3). Overall, the model has good indicator reliability, construct reliability, convergent validity, and discriminant validity. As these criteria are met, the constructs can test the structural model.

### 5.2. Structured model

To evaluate the structured model, we followed Hair's five-step approach (Hair et al., 2013): (1) collinearity assessment, (2) structural model path coefficients, (3) coefficient of determination ($R^2$ value), (4) effect size $f^2$, and (5) predictive relevance $Q^2$ and blindfolding. Regarding collinearity (1), the results suggest minimal collinearity among the constructs (the highest VIF among the explanatory variables is 2.95), which means the predictors in the structural model do not suffer from this issue. To empirically assess the hypotheses postulated in Section 3, the study examines the level of significance in path

**Table 3**
Loadings and cross-loadings for the measurement model.

| Construct | | Item | ENKM | EXKM | KSP | AG | PLP | FP | SP |
|---|---|---|---|---|---|---|---|---|---|
| Endogenous knowledge management | | ENKM1 | **0.715** | 0.171 | 0.270 | 0.264 | 0.240 | 0.266 | 0.180 |
| | | ENKM2 | **0.796** | 0.092 | 0.393 | 0.184 | 0.094 | 0.331 | 0.190 |
| | | ENKM3 | **0.915** | 0.317 | 0.294 | 0.450 | 0.322 | 0.476 | 0.371 |
| | | ENKM4 | **0.826** | 0.313 | 0.135 | 0.374 | 0.331 | 0.508 | 0.365 |
| Exogenous knowledge management | | EXKM1 | 0.086 | **0.797** | -0.183 | 0.390 | 0.365 | 0.328 | 0.345 |
| | | EXKM2 | 0.214 | **0.899** | -0.136 | 0.495 | 0.477 | 0.446 | 0.403 |
| | | EXKM3 | 0.397 | **0.775** | 0.057 | 0.444 | 0.636 | 0.515 | 0.434 |
| Knowledge sharing partners | | KSP1 | 0.383 | −0.012 | **0.873** | −0.125 | −0.140 | −0.167 | −0.156 |
| | | KSP2 | 0.324 | −0.058 | **0.939** | −0.145 | −0.185 | −0.116 | −0.192 |
| | | KSP3 | 0.210 | −0.140 | **0.960** | −0.245 | −0.276 | −0.199 | −0.300 |
| Agility | | AG2 | 0.395 | 0.453 | −0.182 | **0.860** | 0.576 | 0.586 | 0.729 |
| | | AG3 | 0.397 | 0.482 | −0.189 | **0.931** | 0.604 | 0.619 | 0.665 |
| | | AG4 | 0.402 | 0.538 | −0.085 | **0.905** | 0.608 | 0.607 | 0.627 |
| | | AG5 | 0.327 | 0.494 | −0.263 | **0.928** | 0.590 | 0.640 | 0.682 |
| Performance at process level | | PLP1 | 0.315 | 0.629 | −0.231 | 0.676 | **0.951** | 0.571 | 0.563 |
| | | PLP2 | 0.308 | 0.533 | −0.204 | 0.558 | **0.939** | 0.525 | 0.552 |
| Competitive advantage | Financial performance | FP1 | 0.445 | 0.501 | −0.238 | 0.675 | 0.571 | **0.950** | 0.728 |
| | | FP2 | 0.531 | 0.496 | −0.071 | 0.594 | 0.487 | **0.949** | 0.665 |
| | | FP3 | 0.477 | 0.518 | −0.199 | 0.657 | 0.594 | **0.950** | 0.704 |
| | Strategic performance | SP1 | 0.343 | 0.363 | −0.134 | 0.615 | 0.507 | 0.584 | **0.840** |
| | | SP2 | 0.327 | 0.445 | −0.298 | 0.683 | 0.499 | 0.719 | **0.932** |
| | | SP3 | 0.321 | 0.485 | −0.230 | 0.715 | 0.590 | 0.681 | **0.927** |

The figures in bold represents the cross-loadings for the measurement model.

coefficients (2) by means of a bootstrapping technique (Hair et al., 2011; Henseler et al., 2009) with 5000 iterations of re-sampling, with each bootstrap sample constituted by the number of observations (i.e., 175 cases). To have more conservative outcomes, the study uses the *no sign change* option (Hair et al., 2013). Fig. 2 shows the estimated model (path coefficients, $R^2$ and $Q^2$), and Table 5 summarizes the results. Concerning $R^2$ values (3), all dependent variables present reasonable values. In addition, this study calculates the $f^2$ and $q^2$ effect sizes (4). Most of the values of $f^2$ effect size are small, with the exception of agility in process-level-performance and exogenous knowledge management in agility (moderate effects). Last, based on a blindfolding procedure, all $Q^2$ values are above zero, which means the model has predictive power concerning the dependent variables (see Fig. 2).

Fig. 2 summarizes the analysis results as follows: the conceptual model explains 61.8% of the variation in organizational agility. Endogenous Knowledge Management (EnKM) ($\hat{\beta} = 0.155$; $p < 0.01$) and Exogenous Knowledge Management (ExKM) ($\hat{\beta} = 0.248$; $p < 0.001$) are statistically significant in explaining organizational agility (AG). Thus, H1 and H2 are confirmed, whereas knowledge sharing partners (KSP) (H3) is not confirmed. Organizational agility (AG) ($\hat{\beta} = 0.371$; $p < 0.001$) is statistically significant in explaining Process-level Performance (PLP), and consequently H4b is supported. The conceptual model explains 57.8% of the variation in Process-level Performance (PLP). Agility (AG) contributes significantly to explain performance at two levels: Process-level Performance (PLP) ($\hat{\beta} = 0.371$; $p < 0.001$) and Competitive Advantage (CA) ($\hat{\beta} = 0.204$; $p < 0.01$), which confirms H4a and H4b. H5 is not supported, as the effect is statistically not significant (PLP- > CA). The conceptual model explains 77.8% of the variation in Competitive Advantage (CA). The conceptual model substantially explains the variation of all three dependent variables (Chin, 1998b; Henseler et al., 2009).

### 5.3. Mediating effect testing

Based on the guidelines of Hair (Hair et al., 2013), Preacher (Preacher & Hayes, 2008), and Nitzl (Nitzl, Roldán, & Cepeda, 2016), the study evaluates the significance of the mediating effects of organizational agility. Mediation analysis is eligible if the indirect effect is significant. Table 6 presents the results, which fulfill the necessary conditions to perform the mediator assessment. Also, the study calculates variance accounted for (VAF) to determine the size of the indirect effect in relation to the total effect (Hair et al., 2013). The results show that agility can partially mediate the relationship between knowledge assets (endogenous and exogenous knowledge) and performance (process-level performance and competitive advantage), thereby supporting H6a,b and H7a,b. No mediating effects were found between knowledge sharing with

**Table 4**
Correlation matrix, composite reliability (CR), and square root of AVEs.

| | CR | ENKM | EXKM | KSP | AG | PLP | FP | SP |
|---|---|---|---|---|---|---|---|---|
| Endogenous knowledge management (ENKM) | 0.89 | **0.82** | | | | | | |
| Exogenous knowledge management (EXKM) | 0.87 | 0.30 | **0.83** | | | | | |
| Knowledge Sharing with Partners (KSP) | 0.95 | 0.31 | −0.09 | **0.93** | | | | |
| Agility (AG) | 0.95 | 0.42 | 0.54 | −0.20 | **0.91** | | | |
| Process level performance (PLP) | 0.94 | 0.33 | 0.62 | −0.23 | 0.66 | **0.95** | | |
| Financial performance (FP) | 0.97 | 0.51 | 0.54 | −0.18 | 0.68 | 0.58 | **0.95** | |
| Strategic performance (SP) | 0.93 | 0.37 | 0.49 | −0.25 | 0.75 | 0.59 | 0.74 | **0.90** |

(1) First column are CR (composite reliability).
(2) Diagonal elements are square root of average variance extracted (AVE).
(3) Off-diagonal elements are correlations.
The bold figures represent the square roots of AVEs.

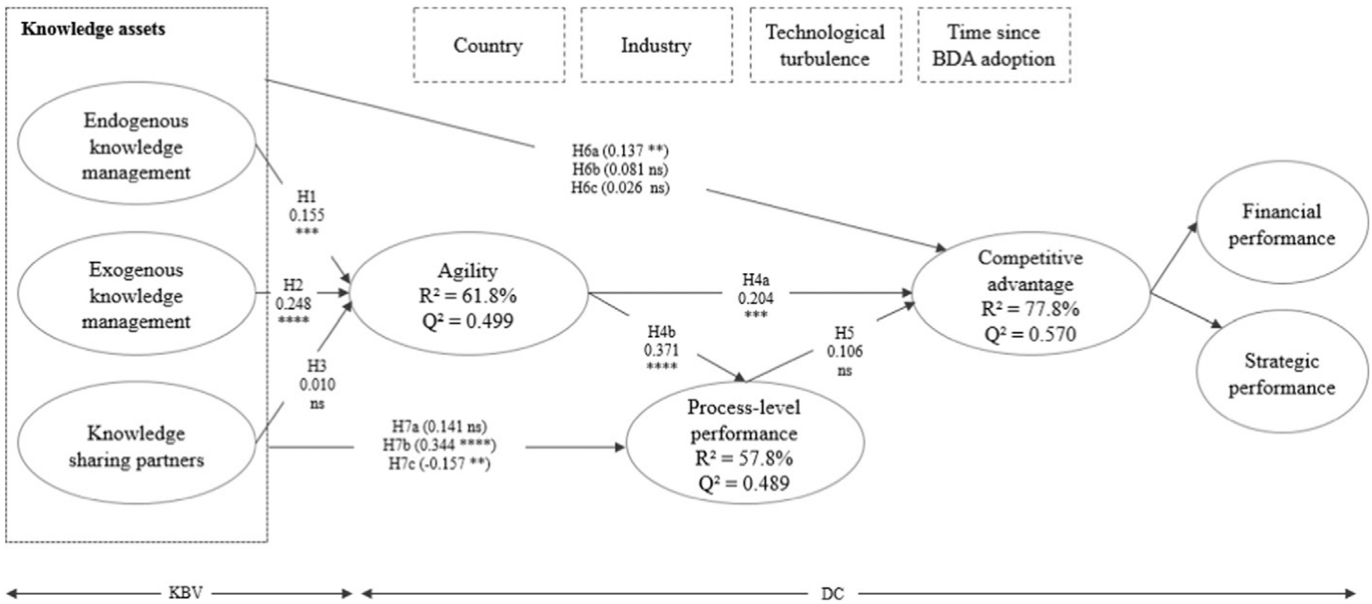


**Fig. 2.** Estimated model. Note: ns = non-significant. ** |t| > =1.96 at p = 0.05; *** |t| > = 2.57 at p = 0.01 level; **** |t| > =3.29 at p = 0.001 level.

partners and performance (process-level performance and competitive advantage), which means H6c and H7c are not confirmed.

## 6. Discussion

As BDA can generate value in several ways, the need exists to understand the entire chain. This study fills the research gap by assessing not only the antecedents but also the effects of BDA initiatives in European firms.

The results strongly support the claim that BDA applications can allow an effective internal and external knowledge management which can help firms to create organizational agility. This agility exists in several ways: (1) by sensing opportunities and threats (e.g., reacting to new products or services of competitors); (2) by seizing possible chances (e.g., expanding into new regional or international markets), and (3) by adjusting to the technological environment to attain competitive advantage (e.g., adopting new technologies to produce products and services more efficiently). This finding is consistent with earlier literature (Chen et al., 2014; Liu et al., 2014; Sher & Lee, 2004).

Regarding the antecedents, the results demonstrate that BDA can support organizational knowledge management, allowing the creation/enhancement of dynamic capabilities such as organizational agility. This finding is consistent with earlier studies applied to IT innovations and organizational management (e.g., (Nieves & Haller, 2014; Sher & Lee, 2004; Cai et al., 2013; Liu et al., 2014; Cepeda & Vera, 2007)). The results suggest that exogenous knowledge management deserves more attention, which was considered more important than endogenous knowledge management. This outcome suggests that BDA technologies can provide business value by facilitating the acquisition of supply chain and marketing knowledge. While knowledge management is important to explain BDA value creation, the way of sharing this strategic asset among business partners is not statistically significant in this study. Although the hypothesis related to the knowledge shared with partners (H3) seems plausible and consistent with earlier studies for other IT innovations (e.g., (Zhu & Kraemer, 2005; Zheng

**Table 5**
Significant testing results of the structural model path coefficients.

| Structural path | Path coefficient (t-value) | Effect size ($f^2$) | Effect size ($q^2$) | 95% confidence interval | Conclusion |
|---|---|---|---|---|---|
| EndKM → AG | 0.155** (2.562) | 0.038 | 0.024 | [0.032; 0.268] | H1 supported |
| ExKM → AG | 0.248**** (4.556) | 0.120 | 0.074 | [0.149; 0.364] | H2 supported |
| KSP → AG | 0.010 ns (0.121) | 0.000 | 0.000 | [−0.145; 0.169] | H3 not supported |
| AG → CA | 0.204*** (2.786) | 0.064 | 0.021 | [0.065; 0.351] | H4a supported |
| AG → PLP | 0.371**** (3.969) | 0.125 | 0.080 | [0.173; 0.544] | H4b supported |
| PLP → CA | 0.106 ns (1.579) | 0.021 | 0.007 | [−0.030; 0.234] | H5 not supported |

Note: ns = non-significant.
The values of $f^2$ and $q^2$ effects can be considered weak (0.02). moderate (0.15) and strong (0.35).
Confidence level:
** |t| > =1.96 at $p$ = 0.05 level.
*** |t| > = 2.57 at $p$ = 0.01 level.
**** |t| > =3.29 at $p$ = 0.001 level.

**Table 6**
Mediation test by bootstrapping approach.

| Effect of | Direct effect (t-value) | Indirect effect (t-value) | Total effect | VAF (%) | Interpretation | Conclusion |
|---|---|---|---|---|---|---|
| EnKM → AG → CA | 0.137** (2.317) | 0.053** (2.156) | 0.190**** (3.577) | 27.89% | Partial mediation | H6a supported |
| ExKM → AG → CA | 0.081 ns (1.506) | 0.097*** (2.617) | 0.178**** (4.037) | 54.49% | Partial mediation | H6b supported |
| KSP → AG → CA | 0.026 ns (0.464) | −0.014 ns (0.607) | 0.012 ns (0.199) | na | No mediation | H6c not supported |
| EnKM → AG → PLP | 0.141** (1.988) | 0.057** (2.212) | 0.198*** (2.813) | 28.79% | Partial mediation | H7a supported |
| ExKM → AG → PLP | 0.344**** (5.412) | 0.092*** (3.041) | 0.436*** (7.219) | 21.10% | Partial mediation | H7b supported |
| KSP → AG → PLP | −0.157** (2.408) | 0.003 ns (0.119) | −0.154** (2.172) | na | No mediation | H7c not supported |

Note: VAF = variance accounted for. The VAF > 80% indicates full mediation. 20% ≤ VAF ≥ 80% show partial mediation. VAF < 20% indicates no mediation. ns = non-significant. na = not applicable.
** |t| > = 1.96 at p = 0.05 level.
*** |t| > = 2.57 at p = 0.01 level.
**** |t| > = 3.29 at p = 0.001 level.

et al., 2011; Ruivo, Oliveira, & Neto, 2014)), this construct does not contribute to creating valuable organizational agility. An earlier study concludes that using this type of knowledge is not always useful and can harm specific business processes in some situations. Moreover, this study shows that agility can partially mediate the positive effect of some knowledge assets (exogenous and endogenous) and performance (process-level performance and competitive advantage) (H6a, H6b and H7a, H6b). This finding is consistent with earlier studies (Liu et al., 2013; Liu et al., 2014; Pavlou & El Sawy, 2006).

Competitive performance is not only about how much firms know, but how they use what they know (Haas & Hansen, 2005). A possible explanation for this result is that firms are reluctant to share sensitive information that might compromise their competitive advantage. In fact, synergies with business partners can be beneficial (e.g.,(Setia, Richardson, & Smith, 2015)), but careful attention is needed regarding the shared information. The study shows that knowledge sharing with partners can be truly compromising in the areas of Production and Operations or Product and Service enhancement, which represent the core business practices of a firm. An information sharing agreement might be a solution to overcome this constraint.

Concerning the effects of agility leveraged by BDA, the results indicate that this dynamic capability can positively impact competitive advantage in different ways (via processes or organizationally), which is in line with the findings of other authors (Drnevich & Kriauciunas, 2011; Protogerou et al., 2012) (H4a,b). Agility can also be more effective in improving specific business processes than organizational performance, which is consistent with Drnevich and Kriauciunas (Drnevich & Kriauciunas, 2011).The results demonstrate that no significant link exists between process-level performance and competitive advantage (H5). In this sense, Drnevich and Kriauciunas (Drnevich & Kriauciunas, 2011) argue that a firm's performance depends on a set of elements that might fail due to miscommunication between the business areas and the top management. Although some business areas can behave in an efficient way, this efficiency does not necessarily have a significant effect on the overall performance.

Although BDA technologies are generaly associated with customer management or marketing areas, results indicate that, in general, European firms focus more on internally improving their assets (products and services) and the way that these are being produced to optimize costs. With Europe still showing signs of financial crisis, this finding might point the way to a change of survival strategy in competitive markets.

### 6.1. Limitations and further research

Certain limitations apply to the interpretation of the results of this study. First, the antecedents of agility do not extend beyond the specific knowledge resources included in the model. Other factors can also determine the development of this dynamic capability in European firms. Future studies may include these resources as variables of the model or by moderating existing variables. Second, although the study considers constructs in the model embedding the impact of BDA at process-level, the model is firm-level. Before generalization is possible, researchers should perform a longitudinal study based on the process approach. Future research should use specific process constructs to assess the impact of BDA on several business areas in detail. Third, due to the perceptual nature of the measures used, future studies should identify the issues associated with cross-sectional research design. Although the use of objective measures to assess firm performance is important, in this study companies were reluctant to provide them. Fourth, although the sample size is statistically adequate, a larger sample could be useful to reinforce the conclusions of this study.

As researchers generally accept that BDA can provide benefits to all European firms (European_Commission, 2015) across several industries, reinforced on a McKinsey survey (Manyika et al., 2011b) reports that most industries in Europe have the capacity to store and manipulate big data, and consequently the potential value of using big data resides mainly in developed countries. Therefore, data from five European developed countries were collected. By conducting future studies in more countries and industries, which may have different perceptions of BDA and diverse external contexts, the understanding of BDA business value could likely improve. Due to their different cultures, research to perform a comparative study among European regions (e.g., Northern and Southern Europe) could be interesting.

### 6.2. Theoretical implications

This study offers two key contributions that extend theory on BDA in technology and organizational management research:

(1) **BDA value chain understanding** - Despite the potential benefits, some firms fail to capture value from BDA initiatives (Kaisler et al., 2013). Recent papers focus on BDA research opportunities (Abbasi et al., 2016; Agarwal & Dhar, 2014), claiming that there is a need to conduct assessments of the actual impact of BDA investments and use, and to understand how to achieve the benefits for performance. The BDA value chain remains relatively unexplored and requires further investigation. The current paper responds to the calls of scholars by empirically assessing the value that BDA can bring to European firms. This study theoretically proposes and empirically validates a conceptual model based on strategic management theories (KBV and DC), never before combined for this purpose, to explain the full BDA value chain. Liu (Liu et al., 2014) argues that literature about the relationship among knowledge management, organizational agility, and firm performance is still limited. This is the first study that empirically demonstrates that BDA applications based on an effective knowledge management can help firms to create organizational agility leading to competitive advantage. Further studies could beneficially use this theoretical framework to assess the business value in other IT innovations at a process-

level and firm-level. Academics can make use of this paper for pedagogical support for teaching about BDA value chain.

(2) **DC literature** – This paper contributes to DC research by empirically testing agility business value in a BDA context (Drnevich & Kriauciunas, 2011). The results strongly support the belief that BDA technologies can trigger agility and that agility can affect competiveness in two ways (via processes or globally). As BDA can significantly improve business processes (Davenport, 2006), business process enhancement driven by BDA is an important research area (Abbasi et al., 2016). Earlier studies focus only on the link between agility and firm performance (Chen et al., 2014; Liu et al., 2014; Tallon & Pinsonneault, 2011), while this study empirically demonstrates that an effect of agility exists at the process-level, too. In addition, despite an increasing use of mediation testing, most of the studies in PLS-SEM do not analyze mediation effects (Hair et al., 2013; Nitzl et al., 2016). Understanding mediation issues can be crucial for researchers because they can better explain or hinder the influence of a third variable in the relationship between two variables in a model (Cepeda & Vera, 2007). This study demonstrates that agility can be a mediator between external and internal knowledge assets and performance (process-level performance and competitive advantage).

### 6.3. Managerial implications

For practitioners (including executives and IT managers) this study demonstrates how best to leverage the knowledge embedded in BDA systems and initiatives and achieve capabilities that will help to maintain competitive advantages. The paper provides support to justify BDA investments and initiatives. The results indicate that although BDA technologies call for substantial investment in implementation and maintenance, European firms are aware of BDA's potential value and benefits. Executives should apply these guidelines to their organizational IT strategy.

BDA can provide value at several stages: (1) knowledge; (2) dynamic capability (organizational agility); (3) business process; and (4) competitive performance. To initiate the value creation process, firms should invest in an effective BDA program. First, the value that BDA can provide derives first from the way firms use the technologies available to manage knowledge. An effective training program can help to leverage the way users extract and manage knowledge. Second, by effectively using BDA, firms can acquire capabilities to innovate and rapidly adjust to external demands (e.g., optimize business processes). Third, these capabilities will encourage specific business areas to involve the whole organization, when an effective bottom-up strategy is followed, supported by good communication practices. By applying this framework to BDA specifically, managers and IT executives can benefit from a performance metric that uniquely specifies the impact of BDA. By evaluating the organizational knowledge conversion into process and firm-level capabilities, practitioners can increase their productivity. Software vendors of BDA can also gain a better understanding of how European firms can invest and experience the value created through BDA. They can natively embed BDA capabilities in their solutions as a way for their customers to achieve superior financial and strategic performance. Finally, firms that have not yet decided to adopt these technologies can gain a perception of what is possible by adopting and effectively using BDA.

### 6.4. Business research implications

The business community now sees big data as a potential tool of business value for achieving competitive advantage. This value can only be real if companies know how to effectively manage Big Data Analytics (BDA) initiatives. This paper establishes a first link between BDA process-level performance and competitive advantage, by merging the field of information systems and strategic management. By presenting and discussing strategic and organizational drivers and impacts of BDA, guidance to business researchers, practitioners, and scholars is provided. As such, this paper extends knowledge by directly evaluating the effect of BDA on the decision-making process to support an effective IT resource management, focusing on challenges for adoption, governance, and evaluation.

The outcomes of this paper indicate that BDA can be an effective aid to survival in competitive markets, particularly by supporting Production and Operations or Product and Service enhancement. Striving to overcome damages of the financial crisis, European firms are using BDA tools to internally improve their assets (products and services) and the way that these are being produced to optimize costs. European firms tend to attribute greater value to external knowledge provided by BDA applications than to internal knowledge management. Sharing knowledge with business partners is potentially harmful to organizational productivity, so careful attention is in order when exchanging this type of core data between companies. Also, this study concludes that organizational agility leads directly to a better performance (process-level and competitive advantage) but can mediate effects from knowledge assets on performance. This means that firms must bear in mind that several paths can lead to competitive advantage. First, managers should consider investing in BDA technologies to take advantage of internal and external knowledge resources. Second, by governing the knowledge extracted by BDA, agility becomes the “ultimate” organizational capability that leads to sustainable competitive advantages. Firms should confidently invest in the development of agility supported by BDA tools.

## 7. Conclusions

As Big Data Analytics (BDA) can offer value to companies in several ways, many scholars highlight the need to understand the path to competitive advantage. The main outcome emerging from this paper has to do with understanding the value chain of BDA. Grounded on knowledge-based view (KBV) and dynamic capabilities (DC), this study fills a research gap from the strategic management perspective, by perceiving the antecedents (knowledge assets) and the impacts (on process-level performance and competitive advantage) of BDA initiatives in European firms. The results show that the model significantly explains all dependent variables (61.8% of agility variation, 57.8% of process-level performance variation, and 77.8% of competitive advantage variation). The major conclusions of this study are:

a) BDA can be a strategic investment for European firms to enhance organizational agility and survive in competitive markets. Firms should invest in the development of organizational agility supported by effective BDA applications.
b) To create agility, European firms tend to believe that the external knowledge deriving from BDA applications can be more effective in the creation of agility than internal knowledge. Sharing knowledge with business partners is problematic, as sharing, is a potential barrier for process-level performance.
c) Regarding the impacts of agility, this capability leads directly to a better performance (process-level and competitive advantage) but can mediate effects from knowledge assets on performance. This means that BDA initiatives can lead to better operational efficiency, but several paths can lead to competitive advantage.

Thus, a crucial need exists for firms to have an integrated view of the BDA chain in order to be able to fully leverage the innovative power of BDA capabilities to achieve competitive advantage.

## Appendix A. Survey questionnaire

| Constructs | Items | Source |
|---|---|---|
| Knowledge assets | Please indicate the extent to which these forms of knowledge are used in your organization. | |
| | BDA technologies: | |
| Endogenous knowledge | ENKM1. Reduce uncertainties of knowledge loss | (Sher & Lee, 2004) |
| | ENKM2. Reduce dependence on specific personnel | |
| Management | ENKM3. Are comprehensively utilized by members in organization | |
| | ENKM4. Are comprehensively constructed in organization* | |
| Exogenous knowledge | EXKM1. Facilitate acquisition of supply chain knowledge | (Sher & Lee, 2004) |
| | EXKM2. Facilitate processing of supply chain knowledge | |
| Management | EXKM3. Facilitate processing of marketing knowledge | |
| Knowledge sharing with channel partners | KSP1. We frequently share knowledge about our business environment (e.g., other business relationships) with our channel partners. | (Liu et al., 2014) |
| | KSP2. Knowledge about all of our channel partners, competitors, etc., is shared with our other channel partners. | |
| | KSP3. Business insights are exchanged between us and our other channel partners. | |
| Organizational agility (dynamic capability) | Please indicate the degree to which the use of BDA tools in the last three years has helped to: | (Lu & Ramamurthy, 2011) |
| | AG1. Respond to changes in aggregate consumer demand.* | |
| | AG2. React to new product or service launches by competitors. | |
| | AG3. Expand into new regional or international markets. | |
| | AG4. Change (i.e., expand or reduce) the variety of products/services available for sale. | |
| | AG5. Adopt new technologies to produce better, faster, and cheaper products and services. | |
| Process-level performance | To what extent has BDA been used to support critical business activities in each of the following processes in the last three years. A sampling of critical activities in each process is shown below. | (Peteraf & Barney, 2003) |
| | PLP1. Production and operations: improve throughout, boost labour productivity, improve flexibility and equipment utilisation, and streamline operations. | |
| | PLP2. Product and service enhancement: embed IT in products, increase pace of development/R&D, monitor design cost, improve quality, support innovation. | |
| | PLP3. Marketing and sales: spot market trends, anticipate customer needs, build market share, improve forecast accuracy, and evaluate pricing options.* | |
| | PLP4. Customer relations: respond to customer needs, provide after-sales service and support, improve distribution, create customer loyalty* | |
| Competitive advantage | Please indicate the degree to which you agree with the following statements. | (Schilke, 2014) |
| | 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. | |
| Control variables | | |
| Time since BDA adoption | Number of years since adoption (#) | |
| Country | Country | |
| Industry | Type of industry | |
| Technological turbulence | Please indicate the degree to which you agree with the following statements. | (Brislin, 1970) |
| | TT1. Extent of technological turbulence in the environment. | |
| | TT2. Leadership in product/process innovation. | |
| | TT3. Impact of new technology on operations. | |

Notes: (1) * items eliminated due 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.

Ambrosini, V., & Bowman, C. (2009). What are dynamic capabilities and are they a useful construct in strategic management? *International Journal of Management Reviews*, *11*(1), 29–49.

Arend, R., & Bromiley, P. (2009). Assessing the dynamic capabilities view: spare change, everyone? *Strategic Organization*, *7*(1), 75.

Barnett, W. P., Greve, H. R., & Park, D. Y. (1994). An evolutionary model of organizational performance. *Strategic Management Journal*, *15*(S1), 11–28.

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

Barua, A., Kriebel, C. H., & Mukhopadhyay, T. (1995). Information technologies and business value: An analytic and empirical investigation. *Information Systems Research*, *6*(1), 3–23.

Bharadwaj, A. S. (2000). A resource-based perspective on information technology capability and firm performance: An empirical investigation. *MIS Quarterly*, *24*(1), 169–196.

Blome, C., Schoenherr, T., & Rexhausen, D. (2013). Antecedents and enablers of supply chain agility and its effect on performance: A dynamic capabilities perspective. *International Journal of Production Research*, *51*(4), 1295–1318.

Brislin, R. W. (1970). Back-translation for cross-cultural research. *Journal of Cross-Cultural Psychology*, *1*(3), 185–216.

Cai, Z., et al. (2013). Developing organizational agility through IT capability and KM capability. *The moderating effects of organizational climate*. PACIS.

Cepeda, G., & Vera, D. (2007). Dynamic capabilities and operational capabilities: A knowledge management perspective. *Journal of Business Research*, *60*(5), 426–437.

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

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., et al. (2014). IT capability and organizational performance: The roles of business process agility and environmental factors. *European Journal of Information Systems*, *23*(3), 326–342.

Chin, W. W. (1998a). *Commentary: Issues and opinion on structural equation modeling*. JSTOR, 7–16.

Chin, W. W. (1998b). *The partial least squares approach for structural equation modeling*.

Chung, T. R. (2010). Knowledge creation and firm performance. In e. (Ed.), *Mediating processes from an organizational agility perspective*. AMCIS.

Corte Real, N., Oliveira, T., & Ruivo, P. (2014). Understanding the hidden value of business intelligence and analytics (BI&A). *Twentieth American Conference of Information Systems*. Savannah, Georgia: Association of Information Systems.

Davenport, T. H. (2006). Competing on analytics. *Harvard Business Review*, *84*, 1–12.

Della Corte, V., & Del Gaudio, G. (2012). Dynamic capabilities: A still unexplored issue with growing complexity. *Corporate Ownership and Control*, *9*, 327–338.

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., et al. (2013). Enhancing the business value of business intelligence: The role of shared knowledge and assimilation. *Journal of Information Systems*, *27*(2), 87–105.

Erevelles, S., Fukawa, N., & Swayne, L. (2016). Big Data consumer analytics and the transformation of marketing. *Journal of Business Research*, *69*(2), 897–904.

Erickson, S., & Rothberg, H. (2015). Big Data and knowledge management: Establishing a conceptual foundation. *Leading issues in knowledge management. Vol. Two*. (pp. 204) 2.

European_Commission (2015). Towards a thriving data-driven economy. Accessed on: 30th December 2015]; Available from http://ec.europa.eu/digital-agenda/en/towards-thriving-data-driven-economy#Article

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*, 375–381.

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.

Goldman, S. L., Nagel, R. N., & Preiss, K. (1995). *Agile competitors and virtual organizations: Strategies for enriching the customer*. Van Nostrand Reinhold.

Grant, R. M. (1996). Prospering in dynamically-competitive environments: Organizational capability as knowledge integration. *Organization Science*, *7*(4), 375–387.

Haas, M. R., & Hansen, M. T. (2005). When using knowledge can hurt performance: The value of organizational capabilities in a management consulting company. *Strategic Management Journal*, *26*(1), 1–24.

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., et al. (2013). *A primer on partial least squares structural equation modeling (PLS-SEM)*. Sage Publications.

Helfat, C., & Peteraf, M. (2009). Understanding dynamic capabilities: Progress along a developmental path. *Strategic Organization*, *7*(1), 91.

Helfat, C. E., et al. (2009). *Dynamic capabilities: Understanding strategic change in organizations*. John Wiley & Sons.

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

IDC (2011). Big Data analytics. *Future architectures, skills and roadmaps for the CIO*.

Kaisler, S., et al. (2013). Big Data: Issues and challenges moving forward. In system sciences (HICSS). *2013 46th Hawaii International Conference on System Sciences*. IEEE.

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.

LaValle, S., et al. (2011). Big Data, analytics and the path from insights to value. *MIT Sloan Management Review*, *52*(2), 21–31.

Liu, H., Song, D., & Cai, Z. (2014). *Knowledge management capability and firm performance: The mediating role of organizational agility*. PACIS.

Liu, H., et al. (2013). The impact of IT capabilities on firm performance: The mediating roles of absorptive capacity and supply chain agility. *Decision Support Systems*, *54*(3), 1452–1462.

Lorenzoni, G., & Lipparini, A. (1999). The leveraging of interfirm relationships as a distinctive organizational capability: A longitudinal study. *Strategic Management Journal*, *20*(4), 317–338.

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

Malladi, S. (2013). Adoption of business intelligence & analytics in organizations–An empirical study of antecedents. *19th American Conference on Information Systems (AMCIS)* Chicago, Illinois.

Manyika, J., et al. (2011a). In M.G. Institute (Ed.), *Big Data: The next frontier for innovation, competition and productivity*. McKinsey Global Institute.

Manyika, J., et al. (2011b). *Big Data: The next frontier for innovation competition and productivity*. McKinsey Global Institute.

Mata, F. J., Fuerst, W. L., & Barney, J. B. (1995). Information technology and sustained competitive advantage: A resource-based analysis. *MIS Quarterly*, *19*(4), 487–505.

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.

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.

Morabito, V. (2015). *Big Data and analytics: Strategic and organizational impacts*. Springer.

Nieves, J., & Haller, S. (2014). Building dynamic capabilities through knowledge resources. *Tourism Management*, *40*, 224–232.

Nitzl, C., Roldán, J. L., & Cepeda, G. (2016). Mediation analyses in partial least squares structural equation modeling. *Helping researchers discuss more sophisticated models* (pp. 3–21).

Nonaka, I. (1995). *The knowledge-creating company: How Japanese companies create the dynamics of innovation*. Oxford University Press.

Pavlou, P. A., & El Sawy, O. A. (2006). From IT leveraging competence to competitive advantage in turbulent environments: The case of new product development. *Information Systems Research*, *17*(3), 198–227.

Pavlou, P. A., & El Sawy, O. A. (2011). Understanding the elusive black box of dynamic capabilities. *Decision Sciences*, *42*(1), 239–273.

Pavlou, P. A., et al. (2005). Measuring the return on information technology: A knowledge-based approach for revenue allocation at the process and firm level. *Journal of the Association for Information Systems*, *6*(7), 199–226.

Peteraf, M. A., & Barney, J. B. (2003). Unraveling the resource-based tangle. *Managerial and Decision Economics*, *24*(4), 309–323.

Pettigrew, A. M., Thomas, H., & Whittington, R. (2001). *Handbook of strategy and management*. Sage.

Podsakoff, P. M., et al. (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., et al. (2012). Towards business intelligence systems success: Effects of maturity and culture on analytical decision making. *Decision Support Systems*, *54*, 729–739.

Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior Research Methods*, *40*(3), 879–891.

Protogerou, A., Caloghirou, Y., & Lioukas, S. (2012). Dynamic capabilities and their indirect impact on firm performance. *Industrial and Corporate Change*, *21*(3), 615–647.

Rajpathak, T., & Narsingpurkar, A. (2013). *Managing knowledge from Big Data analytics in product development*. Tata Consulting, 11.

Ringle, C. M., Sarstedt, M., & Straub, D. (2012). A critical look at the use of PLS-SEM in MIS quarterly. *MIS Quarterly (MISQ)*, 36(1).

Ruggles, R. (1998). The state of the notion: Knowledge management in practice. *California Management Review*, *40*(3), 80–89.

Ruivo, P., Oliveira, T., & Neto, M. (2014). Examine ERP post-implementation stages of use and value: Empirical evidence from Portuguese SMEs. *International Journal of Accounting Information Systems*, *15*(2), 166–184.

Ruivo, P., Oliveira, T., & Neto, M. (2015). Using resource-based view theory to assess the value of ERP commercial-packages in SMEs. *Computers in Industry*, *73*, 105–116.

Russom, P. (2011). *Big Data analytics*. Fourth Quarter: TDWI Best Practices Report.

Ryans, A. B. (1974). Estimating consumer preferences for a new durable brand in an established product class. *Journal of Marketing Research*, 434–443.

Sambamurthy, V., Bharadwaj, A., & Grover, V. (2003). Shaping agility through digital options: Reconceptualizing the role of information technology in contemporary firms. *MIS Quarterly*, 237–263.

Sambamurthy, V., et al. (2007). IT-enabled organizational agility and firms' sustainable competitive advantage. *ICIS 2007 proceedings* (pp. 91).

Saraf, N., Langdon, C. S., & Gosain, S. (2007). IS application capabilities and relational value in interfirm partnerships. *Information Systems Research*, *18*(3), 320–339.

SAS (2013). Big Data analytics. *An assessment of demand for labour and skills, 2012–2017*.

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.

Schryen, G. (2013). Revisiting IS business value research: What we already know, what we still need to know, and how we can get there. *European Journal of Information Systems*, *22*(2), 139–169.

Setia, P., Richardson, V., & Smith, R. J. (2015). Business value of partner's IT intensity: Value co-creation and appropriation between customers and suppliers. *Electronic Markets*, 1–16.

Shanks, G., & Bekmamedova, N. (2013). Creating value with business analytics in the supply chain. *European Conference of Information Systems. Utrecht: European Conference on Information Systems*.

Shanks, G., & Sharma, R. (2011). Creating value from business analytics systems: The impact of strategy. *15th Pacific Asia Conference on Information Systems: Quality Research in Pacific, PACIS 2011* (pp. 1–12). Queensland: Queensland University of Technology.

Sharma, R., Mithas, S., & Kankanhalli, A. (2014). Transforming decision-making processes: A research agenda for understanding the impact of business analytics on organisations. *European Journal of Information Systems*, *23*(4), 433–441.

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.

Soh, C., & Markus, M. L. (1995). How IT creates business value: A process theory synthesis. *International Conference of Information Systems*. ICIS Proceedings.

Tallon, P. P. (2007). A process-oriented perspective on the alignment of information technology and business strategy. *Journal of Management Information Systems*, *24*(3), 227–268.

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).

Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal*, *28*(13), 1319–1350.

Teece, D., Peteraf, M. A., & Leih, S. (2016). Dynamic capabilities and organizational agility: Risk, uncertainty and entrepreneurial management in the innovation economy. *Uncertainty and Entrepreneurial Management in the Innovation Economy (April 7, 2016)*.

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

Volberda, H. W. (1996). Toward the flexible form: How to remain vital in hypercompetitive environments. *Organization Science*, *7*(4), 359–374.

Wade, M., & Hulland, J. (2004). Review: The resource-based view and information systems research: Review, extension, and suggestions for future research. *MIS Quarterly*, *28*(1), 107–142.

Wang, C. L., & Ahmed, P. K. (2007). Dynamic capabilities: A review and research agenda. *International Journal of Management Reviews*, *9*(1), 31–51.
Wang, E., Klein, G., & Jiang, J. J. (2007). IT support in manufacturing firms for a knowledge management dynamic capability link to performance. *International Journal of Production Research*, *45*(11), 2419–2434.
Weill, P., Subramani, M., & Broadbent, M. (2002). Building IT infrastructure for strategic agility. *MIT Sloan Management Review*, *44*(1), 57.
Wu, L. -Y. (2006). Resources, dynamic capabilities and performance in a dynamic environment: Perceptions in Taiwanese IT enterprises. *Information & Management*, *43*(4), 447–454.
Xu, Z., Frankwick, G. L., & Ramirez, E. (2016). Effects of big data analytics and traditional marketing analytics on new product success: A knowledge fusion perspective. *Journal of Business Research*, *69*(5), 1562–1566.
Zheng, S., Zhang, W., & Du, J. (2011). Knowledge-based dynamic capabilities and innovation in networked environments. *Journal of Knowledge Management*, *15*(6), 1035–1051.
Zhou, K. Z., & Wu, F. (2010). Technological capability, strategic flexibility, and product innovation. *Strategic Management Journal*, *31*(5), 547–561.
Zhu, K., & Kraemer, K. (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.
Zollo, M., & Winter, S. G. (2002). Deliberate learning and the evolution of dynamic capabilities. *Organization Science*, *13*(3), 339–351.
Zott, C. (2003). Dynamic capabilities and the emergence of intraindustry differential firm performance: Insights from a simulation study. *Strategic Management Journal*, *24*(2), 97–125.