Making big data analytics perform: the mediating effect of big data analytics dependent organizational agility

Samuel Fosso Wamba[1], *Shahriar Akter*[2] & *Cameron Guthrie*[3]

ABSTRACT

While big data analytics (BDA) has received significant attention from both scholars and practitioners, significant gaps remain in our understanding of how organizations can effectively manage and leverage BDA resources. Drawing on the big data analytics literature and organizational agility literature, this study investigates the impact of BDA capability on firm performance and the mediating effect of organizational agility on this relationship. The proposed model is tested using data collected from 202 firms in the U.S and partial least squares modelling. The results support the research model and confirm the critical role of organizational agility for BDA investments to create strategic business value and improve firm performance.

Keywords: *Big data, big data analytics capability, IT-dependent organizational agility, performance.*

RÉSUMÉ

Bien que le big data analytics (BDA) ait fortement cristallisé l'attention des spécialistes et des praticiens, il est encore difficile de bien cerner la façon dont les organisations peuvent mobiliser et gérer efficacement cet outil. En se fondant sur des travaux réalisés sur le big data analytics et l'agilité organisationnelle, la présente étude explore l'impact de la capacité du BDA sur la performance des entreprises ainsi que l'effet d'intermédiation de l'agilité organisationnelle sur cette relation. Des données collectées auprès de 202 entreprises américaines ont servi à tester le modèle proposé en recourant à l'approche PLS. Les résultats obtenus soutiennent le modèle de recherche choisi et confirment que l'agilité organisationnelle contribue fortement à attirer des investissements dans le BDA en vue de créer une valeur commerciale stratégique et améliorer la performance des entreprises.

Mots-clés : *Big data, capacité big data analytics, agilité organisationnelle dépendante des TI, performance.*

[1] Toulouse Business School, Toulouse, France

[2] Sydney Business School, University of Wollongong, Australia

[3] Toulouse Business School, Toulouse, France

1. INTRODUCTION

The impact of big data analytics (BDA) on firm performance has generated tremendous interest in recent years (Loebbecke and Picot 2015, McCue 2015, Newell and Marabelli 2015). BDA is a holistic process that manages, processes and analyses large (from terabytes to exabytes) and complex (from sensors to social media) datasets in order to create actionable insights for sustained competitive advantages (Chen *et al.* 2012). A recent survey found that 91.7% of Fortune 1000 companies considered big-data initiatives as necessary to stay both agile and competitive in today's business environment (Partners 2019).

BDA has been found to have several organizational impacts including reducing costs and improving supply chain visibility (Lavalle *et al.* 2011; McAfee *et al.* 2012; Verbraken *et al.* 2012), improving customers service and sales (Columbus 2014), improving decision-making quality (Ghasemaghaei *et al.* 2018), operational efficiency (Kiron 2013) and firm performance (Wu *et al.* 2016). Leading firms are currently using their BDA capabilities to improve business processes and launch new BDA-enabled business models (Henke *et al.* 2016). For example, UPS is using its BDA infrastructure to dynamically determine the best routes for its drivers (Shekhar *et al.* 2012), and US-based T-Mobile cut customer defections in half in a single quarter by merging customer information obtained from social media with its intra-organizational systems (Taylor 2012).

While studies have described a positive relationship between BDA and firm performance (Davenport *et al.* 2007a; Vitari *et al.* 2016; Wixom *et al.* 2013), the challenges to wider use of BDA include inadequate infrastructure and data warehouse architecture (Barbierato *et al.* 2014), data quality and integration complexities (Gandomi *et al.* 2015), data security and privacy issues (Barnaghi *et al.* 2013), a lack of skilled talent (Kim *et al.* 2014), data governance problems (Kim *et al.* 2014) and difficulties evaluating the impact of BDA on business value and firm performance (Baesens *et al.* 2014). Ignoring these challenges has sometimes led to spectacular failures such as the NHS patient record system in the UK that was abandoned at a cost of £10 billion (Marr 2018). Although BDA has become more mainstream, these issues are flattening out the steep growth curve of firm performance (Kiron *et al.* 2014). According to Ross *et al.* (2013, p. 93), "big-data initiatives are all the rage, but most companies don't see a return on their analytics investments."

Responding to these challenges requires scholars to ask, "what capabilities (technical and non-technical) should an organization acquire to succeed in big data efforts?" (Phillips-Wren *et al.* 2015, p. 465). One answer could be greater agility within the analytics function. Agility refers to how quickly and effectively a department, function or organization senses and adapts to changes in its environment. While the information systems field has established that organizational agility increasingly depends on IT department agility (Galliers 2007), no studies have examined how the agility of BDA capabilities (BDAGIL) influences the relationship between BDA capabilities (BDAC) and organizational outcomes, notably the creation of strategic business value (SBVAL) and firm performance (FPER). In the same way that organizations are increasingly relying on the agility of the IT function to respond to unanticipated environmental threats and opportunities, so too could they call on big data analytics.

Our research draws on previous studies of BDA capability (BDAC) and organizational agility to address this question. More precisely, this study answers the following research questions:

R1: What is the direct impact of BDAC on BDAGIL, SBVAL and FPER?

R2: Does BDAGIL mediate the relationship between BDAC and FPER, and between BDAC and SBVAL?

The paper is organized as follows. Following the introduction, the paper discusses the nature of BDAC and BDAGIL followed by the theoretical foundation used for the development of the conceptual model and hypotheses. Next, we present the research methodology, followed by the data analysis, findings, and discussion. Lastly, the conclusion presents the research limitations, the theoretical and practical contributions of the study, and future research directions.

2. THEORY AND HYPOTHESES

2.1. Big data analytics capability

Big data analytics involves applying analytical techniques to large and complex sets of data to uncover hidden knowledge, improve decision-making, and support strategic planning (Chiang *et al.* 2018). Organizations with the capacity to manage and analyze big data are expected to generate competitive advantage. Scholars have recently proposed a theory of big data analytics capability, drawing on the resource-based view of the firm and the IT capability literature.

The resource-based view (RBV) provides firms with a powerful perspective to understand the reasons behind success or failure (Lin *et al.* 2014; Srivastava *et al.* 2001), and an improved lens on the possible strategic options available (Wernerfelt 1984). RBV studies a firm from the perspective of its resources rather than of its products and services (Wernerfelt 1984). Scholars following this stream of research argue that an organization's capacity to create a competitive advantage is contingent on its ability to successfully manage its critical resources (e.g., asset, capabilities, firm attributes, information, knowledge, organizational processes) and deploy a "value creating strategy not simultaneously being implemented by any current or potential competitors" (p. 102) (Barney 1991). This competitive advantage, in turn, could lead to improved firm performance (Grant 1991; Newbert 2007). The RBV has been used by scholars from many fields of research including marketing (Srivastava *et al.* 2001), operations management and supply chain (Hitt *et al.* 2016; Hollands 2008), and information systems (Bharadwaj 2000; Kearns *et al.* 2003; Santhanam *et al.* 2003; Wade *et al.* 2004).

Drawing on RBV, IT capability refers to a firm's ability to mobilize and deploy IT-based resources in combination with other resources and capabilities (Bharadwaj 2000). IT capability offers a holistic view of the IT resources that are needed within an organisation to realize and sustain competitive advantage. In the literature, many conceptualizations of IT capability have been proposed. For example, Opresnik *et al.* (2015) propose a conceptualization of IT capability that encompasses flexible IT infrastructure and IT assimilation. A firm's IT infrastructure is defined as "a set of technological resources occurring over time that can be inimitable" (Raschke 2010). A flexible IT infrastructure provides the platform that can help firms "exchange knowledge, align processes, and achieve operation flexibilities" (Opresnik *et al.* 2015). IT assimilation is the ability of an organizational IT infrastructure to affect "the effectiveness and efficiency of business processes within and across organizational boundaries through embedding IT applications into business processes" (Opresnik *et al.* 2015). A combination of IT infrastructure, human IT resources (managerial and technical IT talents) and intangible IT resources (e.g., knowledge assets, customer orientation, and synergy) are necessary to develop IT capability (Bharadwaj 2000; Chae *et al.* 2014). Chen *et al.* (2014) conceptualize IT capability as a second-order construct that has six dimensions: IT infrastructure, IT business partnerships, business IT strategic thinking, IT business process integration, IT management, and external IT linkage. They argue that their conceptualization of IT capability underlines the cohesion and potential synergies that may exist between any given organizational IT resources and assets. Finally, Kim *et al.* (2012) draw on the socio-materiality perspective (Orlikowski 2007) to propose a conceptualization of IT capability focusing on management, technology and personnel capability. The relational ontology of the socio-materiality perspective recognizes that within any given organization, there is a mutual influence between the human (e.g., talent management), organizational (e.g., management), and physical (e.g., infrastructure) dimensions, thus making it difficult to assess the unique contribution of each dimension to organizational performance (Orlikowski *et al.* 2008).

Scholars have built on the RBV and IT capability literature to conceptualize big-data analytics capability. BDAC is defined as "a firm's ability to assemble, integrate, and deploy its big data-specific resource" (Gupta *et al.* 2016) and is often conceptualized as a multidimensional construct. Early work by Davenport *et al.* (2007a) based on case studies and industry experience proposed a two-level hierarchical structure of business analytics capability comprised of human, technological and organizational capabilities. Gupta *et al.* (2016) suggest that firms need a combination of tangible, human, and intangible resources to build a BDA capability. Tangible resources consist of data, technology, and time spent on BDA projects. Human resources include managerial and technical big data skills. Intangible resources include a data-driven culture and the level of organizational learning. Akter *et al.* (2016) draw on the socio-materialism perspective to capture the "entangled" nature of big data analytics capability. BDAC is conceptualized as a third order construct consisting of three primary dimensions (i.e., management, technology, and talent capability) and 11 subdimensions (i.e., planning, investment, coordination, control, connectivity, compatibility, modularity, technology management knowledge, technical knowledge, business knowledge and relational knowledge). Key big data analytics capability dimensions are inextricably intertwined and mutually supportive to allow for improved business value and sustained competitive advantage (Kohli *et al.* 2008). For example, BDA management capability, encompassing planning, investment, coordination, and control, ensures that a firm's overall analytics strategy is aligned with business opportunities (Barton *et al.* 2012), that the required investments are made to capture these opportunities, and that necessary coordination and control mechanisms are designed and deployed to leverage these analytics investments (Davenport *et al.* 2007b).

Following Braun and Clarke's (2006) guidelines, we conducted a thematic analysis of the extant literature on big data analytics capability (n=20). The results lend support to Akter and colleagues conceptualization of BDAC (Akter *et al.* 2016). We used Krippendorff's alpha (or, Kalpha) (Krippendorff 2004; Krippendorff 2007) to measure the reliability of the thematic analysis, as recommended by Hayes (2011) and De Swert (2012). The Kalpha value is calculated based on the inter-rater reliability score of the coded variables (Hayes *et al.* 2007). To estimate the Kalpha, each of the subthemes was coded independently by two "judges" using a nominal scale ranging from 1 to 3 (i.e., 1= BDA management capability, 2= BDA infrastructure capability, 3= BDA talent capability). The computed Kalpha value of 0.86 exceeds the cut off value of 0.80 and attests to the validity of the thematic analysis (De Swert 2012) and confirms that BDAC is a higher-order multidimensional construct.

According to the resource-based view, organizations that successfully manage their critical big data analytics resources are well positioned to create competitive advantage and consequently improve firm performance. BDA gives firms a competitive advantage if it is used to create strategic business value (SBVAL), including both functional value (e.g. market share) and symbolic value (e.g. positive brand image) (Grover *et al.* 2018). Recent studies have shown that BDA capability indeed has a positive impact on FPER (Akter *et al.* 2016; Fosso Wamba *et al.* 2017; Müller *et al.* 2018). Studies are yet to empirically examine the impact of BDAC on SBVAL creation.

The present study contributes to the emerging BDA literature by examining the direct effects of BDAC on both SBVAL and FPER. It is therefore hypothesized that:

H1: BDAC has a significant positive impact on SBVAL.

H2: BDAC has a significant positive impact on FPER.

H3: SBVAL has a significant positive impact on FPER

2.2. Organizational agility and big data analytics

Firms can use the insights generated through big-data analytics to increase their agility. Organizational agility refers to the ability to detect changes, opportunities, and threats in a business environment and to adapt by reconfiguring resources and processes (Holsapple *et al.* 2009). An organization is considered agile if its response to change is quick and effective. The IT literature views organizational agility as an extension of organizational flexibility that allows an organization to embed enabling mechanisms into organizational processes and IT systems with a view to responding to both unexpected and predictable changes in the marketplace (Lu and Ramamurthy, 2011). IT driven organizational adaptation has been called IT-dependent organizational agility and defined as "the ability to respond operationally and strategically to changes in the external environment through IT" (Fink *et al.* 2007).

Early studies found that IT capability has a positive relationship with organizational agility, which in turn impacts organizational performance (Swafford *et al.* 2006). Lu and Ramamurthy (2011) found a positive link between IT capability and organizational agility and encouraged firms to continue investing in the development of superior IT capability that will provide them with enough flexibility to manage and use their resources effectively in order to build agile organizations. Felipe *et al.* (2016) observed 172 Spanish senior managers and found a positive relationship between IT capability and organizational agility.

In a similar spirit, we propose the concept of BDA-dependent organizational agility (BDAGIL) as the ability to use big-data analytics to respond quickly and effectively at operational and strategic levels to changes in the external environment. Following work on IT-dependent organizational agility, big data analytics can be used to enhance a firm's agility so long as BDA systems and information use practices are also agile. This conceptualization appears consistent with practice. For example, based on a study of business analytics best practices of 23 North American companies, Wixom *et al.* (2013) identify two ways IT leaders maximize the value from business analytics investments: reducing the time it takes to transform data into usable information and deepening the usage of analytics across the enterprise. Consistent with previous conceptualizations of IT-dependent organizational agility and notably Fink *et al.* (2007), BDA-dependent organizational agility is conceptualized as a second-order construct of three interrelated first-order constructs: strategic agility, information agility, and system agility. Strategic agility is the ability to respond efficiently and effectively to emerging market opportunities by taking advantage of existing BDA capabilities. Information agility refers to the ability to easily change the way users access and consume BDA resources, and system agility is the ability adapt and evolve BDA systems without incurring significant penalties in time or cost.

Drawing on the IT capabilities and organizational agility literatures, we argue that BDAC can be used to enhance overall organizational agility in a data-driven economy. BDA can provide timely insights into operational processes and environmental conditions that can increase the rapidity and effectiveness of organizational decision-making. For example, Côrte-Real *et al.* (2017) surveyed IT and business executives in 175 European firms and found that BDA applications enhanced organizational agility by improving internal and external knowledge management. The authors exhorted firms to view BDA as a strategic investment "to enhance organizational agility and survive in competitive markets" (p. 387). It is therefore hypothesized that:

H4: BDAC has a significant positive impact on BDAGIL.

H5: BDAGIL has a significant positive impact on SBVAL.

H6: BDAGIL has a significant positive impact on FPER.

2.3. Big data analytics agility as a mediator between capabilities and outcomes

Prior studies have established a mediating effect of agility on the relationship between IT capabilities on business outcomes. Opresnik *et al.* (2015) used the dynamic capabilities perspective and the view of a hierarchy of capabilities to develop a research model that examines the impact of IT capability on FPER and the mediating effect of absorptive capacity and supply chain agility on this relationship. Their results confirmed a full mediating effect of supply chain agility on the relationship between IT capability and FPER. Tallon *et al.* (2011) tested a research model in which agility mediated the link between alignment and FPER under varying conditions of IT infrastructure flexibility and environmental volatility. The authors used data from a matched survey of IT and business executives in 241 firms and found a positive and significant relationship between IT alignment and agility and between agility and FPER. The effect of IT alignment on performance was fully mediated by agility. Based on a survey of 400 full-time IT managers and professionals, Lowry *et al.* (2016) found that IT agility mediates the relationship between internal IT service perceptions and IT service quality. Using data collected from 250 firms in Taiwan's glass industry, Yang *et al.* (2012) found that a firm's agility capability was a critical competitive strategy source of firm performance. The authors argued that by strengthening their agility, organizations will be in a better position to deal with unpredictable changes in the marketplace. Fink *et al.* (2007) examined cross-sectional data collected from 293 IT managers in Israel and concluded that IT is commonly considered to be an enabler of organizational agility since IT can foster the creation of strategic and operational benefits. Chen *et al.* (2014) concluded that "IT capability can affect firm performance through the mediating role of other resources or capabilities. Business process agility, as a strategic capability, depends on a firm's ability to implement and leverage IT resources" (p. 330).

Similarly, Côrte-Real *et al.* (2017) found that organizational agility partially mediates the effect between knowledge assets such as BDA technologies, process level performance and competitive advantage. Fosso Wamba *et al.* (2017) found that process-oriented dynamic capabilities played a strong mediating role in improving insights from BDAC and enhancing FPER. Process oriented dynamic capabilities refer to "a firm's ability to change (improve, adapt, or reconfigure) a business process better than the competition in terms of integrating activities, reducing cost, and capitalizing on business intelligence/learning" (Kim *et al.* 2011). Both BDAC and process-oriented dynamic capabilities explained 65% of the variance of firm performance of which 30% was explained by the mediator.

Based on the above discussion, we propose that:

H7: BDAGIL mediates the influence of BDAC on SBVAL.

H8: BDAGIL mediates the influence of BDAC on FPER.

To summarize, the conceptual framework for our hypotheses is presented in Figure 1.

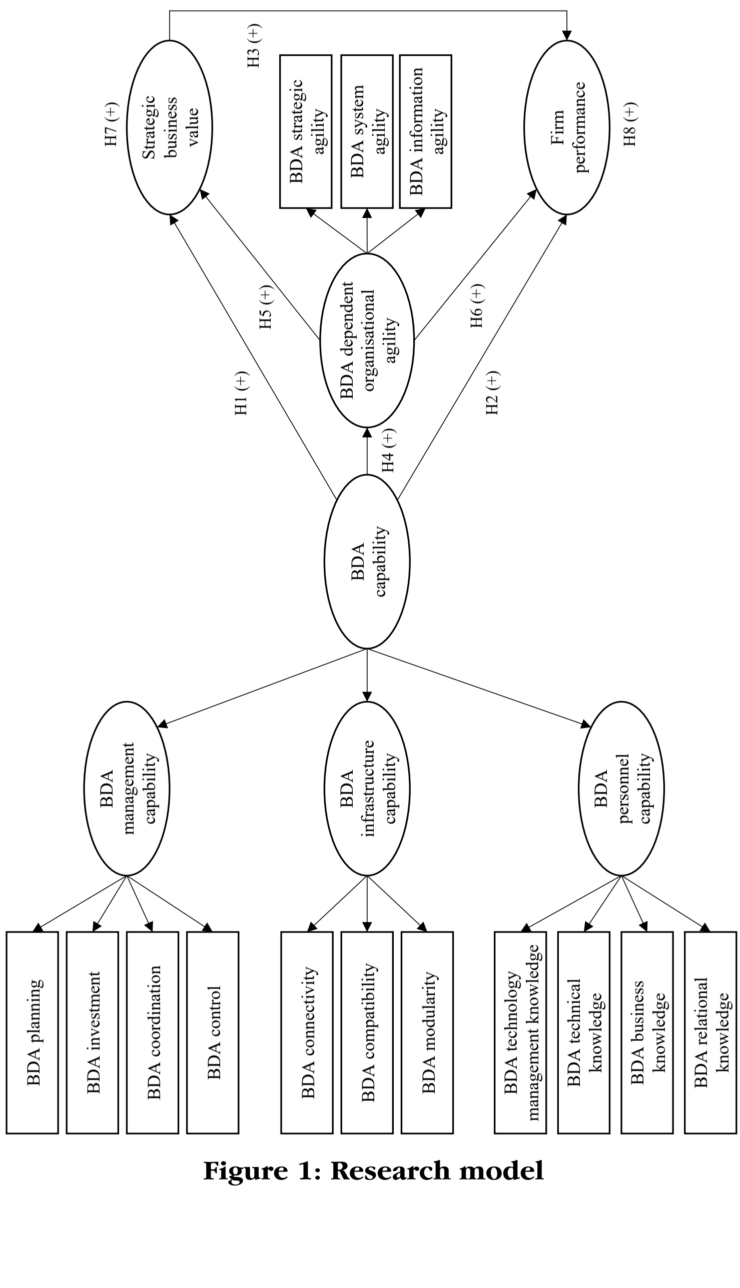

Figure 1: Research model

3. STUDY DESIGN AND METHOD

3.1. Research design

This study is part of a larger research project investigating the adoption and use of BDA. A web-based survey approach was employed to collect data using instruments from the extant literature or specifically developed for the purposes of the study. Structural equation modelling (SEM) was used to test the conceptual model. To establish parsimony in theory validation and reduce the complexity of a large model, the study used partial least squares based structural equation modelling (PLS-SEM). We opted for PLS-SEM because it is robust in estimating large models and avoids limitations regarding distributional assumptions, model identification and factor indeterminacy (Hair *et al.* 2011).

3.2. Measurement

All items used in the study were measured using a seven-point Likert scale with anchors ranging from strongly disagree (1) to strongly agree (7). Survey items are reproduced with references to base sources in Appendix A.

Big data analytics capability

Consistent with the extant literature (Akter *et al.* 2016; Fosso Wamba *et al.* 2017), BDA capability (BDAC) is considered to be a third-order, hierarchical construct with three second-order constructs (BDA management capability, BDA infrastructure capability, and BDA personnel expertise capability) and eleven first-order constructs (BDA planning, investment, coordination, control, connectivity, compatibility, modularity, technical knowledge, technology management knowledge, business knowledge and relational knowledge). The items used to measure each of the first order constructs were taken from Akter *et al.* (2016).

Big data analytics dependent organizational agility

Following Fink and Neumann's (2007) conceptualization of IT-dependent organizational agility, BDA-dependent organizational agility (BDAGIL) is conceptualized as a second-order construct of three interrelated first-order constructs: system agility, information agility, and strategic agility. The items used to measure each of the first-order constructs were adapted to the BDA context from Fink *et al.* (2007).

Performance outcomes

FPER is measured based on how well big data analytics allows firms to perform relative to competitors. The three items used to measure FPER were adapted from Tippins *et al.* (2003).

The SBVAL construct was developed for the purposes of the study to capture the value that accrues from the use of BDA. Three items pertaining to the rapidity of response to change and reactivity to customer demand were used.

3.3. Data collection

Data were collected from the U.S.A. in July 2016 by a leading market research firm. The population was defined as analytics professionals in mid-level management with previous experience of business analytics projects. This population was chosen as they are expected to be knowledgeable of analytics resources, processes and impacts at an operational level, and thus capable of evaluating both big data analytics capability and agility.

The questionnaire was pre-tested using 20 random samples to ensure that question content, wording, sequencing, format and layout, difficulty, instructions, and the range of the scales (5-point vs. 7-point) were appropriate. Once the questionnaire was finalized using feedback from the pretest, an invitation to participate in the study was sent to a research panel of 538 analytics professionals who had agreed to participate in the study. A total of 202 questionnaires were considered valid and appropriate for further analysis.

In order to address the concern of non-response bias we first compared the profiles of the sample respondents with those in the panel in terms of organizational size and industry type; and found no evidence of bias. We then used paired t-tests to check for differences between early (25%) and late (25%) responses on survey items. Again, no non-response bias was found (Akter *et al.* 2016; Stanko *et al.* 2012). The study also addressed the problem of common method variance (CMV) via research design and robust statistical procedures. The questionnaire was designed to psychologically separate exogenous and endogenous variables so that respondents could not establish a causal relationship between them, to guarantee anonymity, and to encourage honest responses by providing clear directions that both positive and negative answers were possible. We also revised and updated the wording of items following the pre-test. With regard to statistical approaches, Herman's single-factor test, did not reveal any factor contributing to more than 30% of total variance (Podsakoff *et al.* 1986). To address the criticism of Herman's single-factor test as an insensitive technique to detect small CMV (Malhotra *et al.* 2006), we applied the marker variable technique (Lindell *et al.* 2001) by including a weakly related item as a marker variable in the SEM model. The findings showed an insignificant relationship between the marker variable and the constructs with an average correlation coefficient of 0.075, and an average t-statistic of 0.343 ($p > 0.05$). Thus, both research design and statistical approaches confirm that there was no CMV in the study.

3.4. Data analysis

Using the repeated indicator approach proposed by Wetzels *et al.* (2009) and Becker *et al.* (2012), this study repeatedly estimated the measurement items for the first-order, second-order and the highest order model. The nature of the model is identified as reflective because the items manifest the constructs and causality is directed from the constructs to the measures. The study used SmartPLS 3.0 (Ringle *et al.* 2014) to estimate the measurement and structural model following guidelines for hierarchical modelling (Becker *et al.* 2010; Chin 2010). An equal number of indicators were repeatedly applied to estimate the scores of first-order and second-order constructs in order to create the highest-order BDAC construct that consists of all the items of the underlying first-order constructs.

4. RESULTS

4.1. Respondent characteristics

Table 1 presents the demographic features of the 202 respondents. The sample includes a wide range of organizations from various industries covering all employment ranges. The majority of respondents were well educated, aged above 40 and had been working for their company for between 2 and 10 years. There was a similar number of male and female individuals in the sample.

Table 1: Demographic profile of the sample

Dimensions	n	%
Gender		
Male	105	52
Female	97	48
Age		
18-25	0	0
26-33	37	18.3
34-41	47	23.3
42-49	39	19.3
50+	79	39.1
Educational level		
No formal education	2	1
Primary	12	5.9
Secondary	21	10.4
Tertiary	167	82.7
Number of years working in the organization		
Less than one year	6	3.0
2-10 years	112	55.4
11-20 years	50	24.8
Over 20 years	34	16.8
Industry		
Accommodation and food service activities	13	6.4
Administrative and support service activities	16	7.9
Electricity, gas, steam and air conditioning supply	15	7.4
Financial and insurance activities	25	12.4
Information and communication	27	13.4
Mining and quarrying	16	7.9
Real estate activities	14	6.9
Water supply; sewerage, waste management	10	5
Wholesale and retail trade; vehicle repair	29	14.4
Other	37	18.3
Size		
0-19	15	7.4
20-99	34	16.8
100-499	44	21.8
500-2499	44	21.8
2500+	65	32.2

4.2. Validity and reliability tests on the measurement model

The study applied a path weighting scheme for structural model approximation and nonparametric bootstrapping (Chin 1998a; Efron *et al.* 1993; Tenenhaus *et al.* 2005) with 5,000 subsamples to obtain the statistical significance for the level of t-statistics (Hair *et al.* 2017). Table 2 shows that all loadings of the first-order constructs are greater than 0.65 and were significant at $p < 0.001$. In addition, composite reliability (CR) and average variance extracted (AVE) of all first-order constructs are above the threshold of 0.80 and 0.50 respectively (Fornell *et al.* 1981; Hair *et al.* 2017). With regard to formative control variables, estimated factor weights of firm size and type all indicate satisfactory collinearity as the variance inflation factor (VIF) scores were below 5.

Table 2: Measurement Model: Assessment of First-Order, Reflective Model

Reflective Constructs	Items	Loadings	CR	AVE
BDA Planning (BPLAN)	BPLAN1 BPLAN2 BPLAN3 BPLAN4	0.844 0.906 0.862 0.846	0.922	0.811
BDA Investment Decision Making (BIDMK)	BIDMK1 BIDMK2 BIDMK3 BIDMK4	0.798 0.842 0.885 0.874	0.938	0.792
BDA Coordination (BCORD)	BCORD1 BCORD2 BCORD3 BCORD4	0.784 0.819 0.862 0.832	0.927	0.760
BDA Control (BCONT)	BCONT1 BCONT2 BCONT3 BCONT4	0.842 0.856 0.879 0.870	0.945	0.811
BDA Connectivity (BCONN)	BCONN1 BCONN2 BCONN3 BCONN4	0.723 0.675 0.750 0.717	0.874	0.635
BDA Compatibility (BCOMP)	BCOMP1 BCOMP2 BCOMP3 BCOMP4	0.864 0.846 0.872 0.797	0.936	0.785
BDA Modularity (BMODU)	BMODU1 BMODU2 BMODU3 BMODU4	0.723 0.675 0.750 0.717	0.935	0.782
BDA Technology Management Knowledge (BTMGM)	BTMGM1 BTMGM2 BTMGM3 BTMGM4	0.851 0.837 0.862 0.844	0.938	0.790
BDA Technical Knowledge (BTKNO)	BTKNO1 BTKNO2 BTKNO3 BTKNO4	0.810 0.862 0.897 0.881	0.944	0.809

BDA Business Knowledge (BBUKN)	BBUKN1 BBUKN2 BBUKN3 BBUKN4	0.795 0.886 0.882 0.869	0.942	0.802
BDA Relational Knowledge (BREKN)	BREKN1 BREKN2 BREKN3 BREKN4	0.846 0.844 0.832 0.815	0.931	0.772
System Agility (SYAGL)	SYAGL1 SYAGL2 SYAGL3 SYAGL4	0.808 0.798 0.810 0.796	0.927	0.760
Information Agility (INAGL)	INAGL1 INAGL2 INAGL3 INAGL4	0.857 0.874 0.852 0.866	0.944	0.808
Strategic Agility (STAGL)	STAGL1 STAGL2 STAGL3 STAGL4	0.844 0.835 0.794 0.833	0.927	0.762
Strategic Business Value (SBVAL)	SBVAL1 SBVAL2 SBVAL3	0.929 0.899 0.904	0.958	0.851
Firm Performance (FPER)	FPER1 FPER2 FPER3	0.926 0.843 0.767	0.928	0.812

The square root of each construct's AVE value was greater than its highest correlation with any other construct (table 3) supporting the discriminant validity of the constructs (Chin 1998b; Chin 2010; Fornell *et al.* 1981). An analysis of cross-loadings also supports discriminant validity as items are more correlated with their own constructs than with others (Chin 2010). Thus, the findings provide adequate evidence of reliability, convergent and discriminant validity of the first-order measurement model.

Table 4 shows the results of higher-order constructs which have been estimated using repeated measurement procedures. The path coefficients between the third-order, second-order and first-order constructs are all significant ($p < 0.001$). The variance of the third-order construct was also satisfactorily explained by its second-order components, that is, MANCAP (91%), TECCAP (90%), and TALCAP (93%).

4.3. Structural model tests and results

After successfully testing the properties of the measurement model, we assessed the validity of the structural model by estimating the path coefficients and t-statistics (table 5), the coefficient of determination (R^2) (Falk *et al.* 1992) (figure 2) and the Stone-Geisser (Q^2) (Geisser 1975; Stone 1974) criterion. The findings reveal significant ($p < 0.05$) standardized path coefficients of 0.342 from BDAC to SBVAL, 0.302 from BDAC to FPER, and 0.210 from SBVAL to FPER thus confirming hypotheses H1, H2 and H3. The path coefficients of 0.687 from BDAC to BDAGIL, 0.407 from BDAGIL to SBVAL, and 0.239 from BDAGIL to FPER were also significant ($p < 0.05$) thus supporting H4, H5 and H6.

Table 3: Correlations and average variance extracted (Square root of AVE on diagonal)

	SBVAL	BBUKN	BCOMP	BCONN	BCONT	BCORD	BIDMK	FPER	INAGL	BMODU	BPLAN	BREKN	SYAGL	STAGL	BTKNO	BTMGM	COVA
SBVAL	**0.922**																
BBUKN	0.533	**0.896**															
BCOMP	0.459	0.591	**0.886**														
BCONN	0.512	0.530	0.404	**0.797**													
BCONT	0.401	0.447	0.512	0.460	**0.901**												
BCORD	0.515	0.598	0.566	0.497	0.484	**0.872**											
BIDMK	0.393	0.535	0.535	0.481	0.566	0.552	**0.890**										
FPER	0.552	0.490	0.498	0.507	0.468	0.374	0.516	**0.901**									
INAGL	0.560	0.488	0.444	0.447	0.537	0.519	0.493	0.533	**0.899**								
BMODU	0.487	0.421	0.493	0.681	0.467	0.533	0.524	0.470	0.467	**0.884**							
BPLAN	0.433	0.525	0.500	0.538	0.585	0.585	0.482	0.482	0.465	0.565	**0.901**						
BREKN	0.516	0.445	0.446	0.454	0.409	0.401	0.547	0.513	0.557	0.480	0.477	**0.879**					
SYAGL	0.502	0.498	0.500	0.494	0.546	0.533	0.493	0.477	0.472	0.506	0.445	0.555	**0.872**				
STAGL	0.459	0.495	0.434	0.421	0.558	0.502	0.539	0.552	0.415	0.477	0.454	0.490	0.436	**0.873**			
BTKNO	0.518	0.426	0.425	0.588	0.435	0.591	0.422	0.511	0.478	0.488	0.501	0.456	0.514	0.493	**0.899**		
BTMGM	0.587	0.424	0.448	0.453	0.419	0.476	0.561	0.532	0.555	0.488	0.578	0.406	0.593	0.571	0.410	**0.889**	
COVA	0.173	0.089	0.195	0.213	0.176	0.108	0.232	0.229	0.230	0.150	0.272	0.145	0.140	0.279	0.213	0.209	**n.a.**

Table 4: Higher-order Model

Models	Latent constructs	Relationships with first-order dimensions	β	R^2	t-stat
Third-order	Big Data Analytics Capability (BDAC)	Management capability Technology capability Talent capability	0.913 0.900 0.937	0.833 0.810 0.879	61.638 57.299 109.789
Second-order	Management Capability (MANCAP)	Planning Decision Making Coordination Control	0.839 0.820 0.862 0.871	0.704 0.673 0.743 0.758	33.072 23.533 44.968 44.539
	Technology capability (TECCAP)	Compatibility Connectivity Modularity	0.930 0.858 0.922	0.864 0.735 0.850	88.386 29.890 80.701
	Talent capability (TALCAP)	Tec. knowledge Tech. mgmt. knowledge Business knowledge Relational knowledge	0.902 0.943 0.902 0.903	0.814 0.890 0.814 0.816	59.155 108.32 53.038 55.228
	BDA-Dependent Organizational Agility (BDAGIL)	System agility Information agility Strategic agility	0.887 0.892 0.913	0.787 0.795 0.833	49.967 51.837 52.345

Table 5: Results of the Structural Model

Hypothesis	Main Model	Path coefficient	Standard error	*t*-statistic
H1	BDAC → SBVAL	0.342	0.110	3.093
H2	BDAC → FPER	0.302	0.100	3.028
H3	SBVAL → FPER	0.210	0.100	2.097
H4	BDAC → BDAGIL	0.687	0.042	16.248
H5	BDAGIL → SBVAL	0.407	0.122	3.331
H6	BDAGIL → FPER	0.239	0.120	1.988

In order to estimate the mediating effect between BDAC-BDAGIL-SBVAL (H6) and BDAC-BDAGIL-FPER (H7), the study followed the procedures outlined by Preacher *et al.* (2008) and Hayes *et al.* (2011) and bootstrapped the sampling distribution of indirect effects using a 95% confidence interval. The mediated path of 0.280 ($p < 0.05$) from BDAC via BDAGIL to SBVAL is the product of the path coefficients from BDAC to BDAGIL and from BDAGIL to SBVAL (table 6). Similarly, we estimated the mediated path from BDAC via BDAGIL to FPER to be 0.164 ($p < 0.05$). Since both direct and indirect effects are significant and positive, the findings in tables 5 and 6 provide strong support for BDAGIL as a partial mediator (Hair *et al.* 2017) and thus support H6 and H7.

Using the coefficient of determination, the study also estimated the overall variance explained by the model at 0.472 for BDAGIL, 0.473 for SBVAL, and 0.436 for FPER. These are identified as large effect sizes according to the R^2 guidelines set out by Cohen (1988). We also tested the predictive validity of the nomological model by estimating Stone-Geisser's Q^2 statistic. The values varied between 0.271 and 0.637, confirming the adequate predictive validity of the model (Chin 2010). These findings provide solid evidence of the influence of big data analytics capability on big data agility, strategic business value and firm performance.

Table 6: Results of mediation testing (BDAGIL)

Path	Direct effect	95% C.I.	t-value	Sig. (p<0.05)	Indirect effect	95% C.I.	t-value	Sig. (p<0.05)
BDAC → SBVAL (H7)	0.342	0.146-0.533	3.259	0.001	0.280	0.119-0.462	3.155	0.002
BDAC → FPER (H8)	0.302	0.114-0.493	2.987	0.003	0.165	0.149-0.457	2.118	0.030

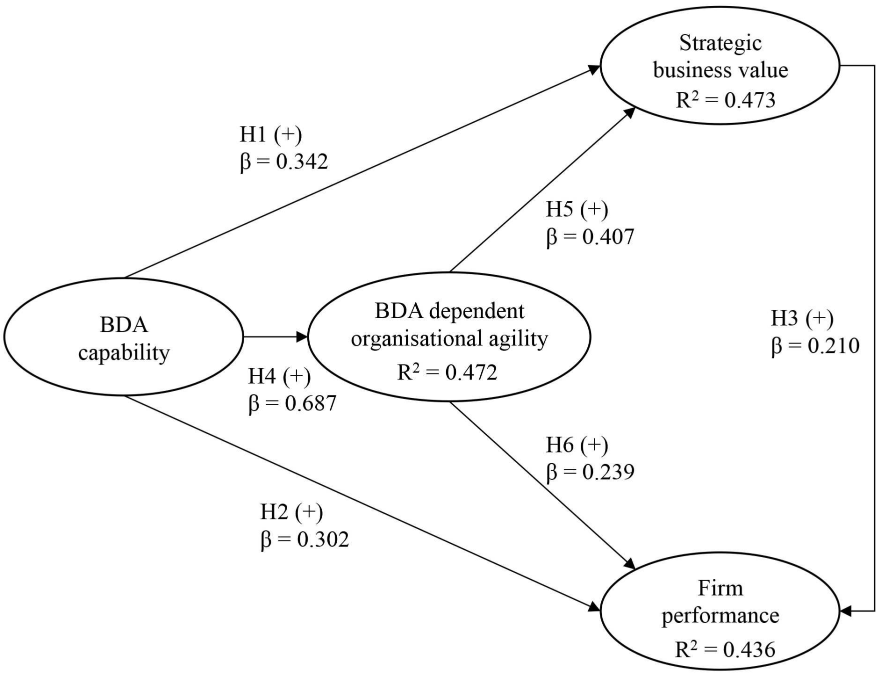

Figure 2: Structural model

5. DISCUSSION

This study drew on the emerging literature on BDA and the IT-dependent organizational agility literature to assess the impact of BDA capability on FPER and the mediating effects of BDA-dependent organizational agility and strategic business value. The analysis of data collected from 202 data analytics professionals in the U.S. provides support for all proposed hypotheses. Overall, the results show that BDAC has a significant positive impact on SBVAL, BDAGIL, and FPER. BDA agility was found to be a strong mediator of both the relationships between BDAC and FPER and between BDAC and SBVAL. Strategic business value is also a strong mediator of the relationship between BDAC and FPER. Finally, the study confirms that management capability, talent capability and technology capability are key dimensions of BDAC: Talent capability was the most important dimension (β=0.937), followed by management capability (β=0.913) and technology capability (β=0.900).

5.1. Implications for research

The present study makes some important theoretical contributions. Firstly, our work extends the concept of IT agility (Fink *et al.* 2007) to a big data context. We find BDAGIL to be a key mediator of the relationship between BDAC, SBVAL and FPER. This result contributes to the growing body of BDA literature by empirically confirming that organizations can improve SBVAL and FPER by leveraging BDA-dependent organizational agility to respond more quickly and effectively to changes, opportunities and threats in internal and external conditions. Future research could investigate the different influences on BDA agility in organizations, and notably the systems, information, and strategic agility of big data systems.

Secondly, this study builds on the emerging BDAC literature and lends support to the usefulness and reliability of Akter *et al.*'s entanglement conceptualization of this construct in measuring organizational big data analytics capabilities (Akter *et al.* 2016). Our results also underscore the dominant role of talent management capability in the BDAC construct, as previously observed by Fosso Wamba *et al.* 2017.

Thirdly, our findings extend prior research on the relationship between IT capability and firm performance (Bharadwaj 2000; Kim *et al.* 2012; Mikalef *et al.* 2017) and between BDAC and firm performance (Akter *et al.* 2016; Gupta *et al.* 2016) by identifying and integrating two mediating factors, namely BDAGIL and SBVAL. By examining the indirect benefits of BDAC (Mooney *et al.* 1996) our results provide valuable insights into the effects of BDA investments on firm performance.

A fourth contribution is the confirmation of the significant mediating role that SBVAL plays in the relationship between BDA and FPER. Analytics investments were found to improve firm performance both directly and by supporting the pursuit of strategic goals and value creation. Our work responds to calls for more empirical research on the ways organizations realize value from big data and analytics (George *et al.* 2014; Günther *et al.* 2017).

5.2. Implications for practice

Our results have several managerial implications. Firstly, our findings may serve as a guideline to practitioners and managers exploring the potential of BDA. Our findings notably suggest that investing in BDA-dependent organizational agility leads to improved firm performance. Firms should pay attention to each of the key components of BDA agility – system agility, information agility, and strategic agility – when investing in BDA. Managers could improve system agility by putting in place processes and methods to accelerate and reduce the cost of big data analytics application maintenance, enhancement and development. This would allow analytics applications to be developed and adjusted rapidly and cost effectively in response to changing internal and external conditions, thereby enhancing the strategic agility of big data analytics systems. IT managers should also ensure that BDA systems are accessible, that insights are shared across the organization and that employees are trained to use applications.

Secondly, this study highlights the key BDAC dimensions that managers should focus on when designing and implementing BDA projects. Managers need to pay attention to the three interrelated BDAC components: management capability, which involves BDA planning, BDA decision-making, BDA coordination and BDA control; technology capability; and talent capability. The latter, probably the most important dimension which managers should focus on, involves the development of technical, managerial, business, and relational BDA knowledge.

5.3. Limitations and future research directions

The present study is constrained in three ways. Firstly, the study follows a cross-sectional approach which only allows the collection of data about the phenomena under study at one moment in time. Future research could employ a longitudinal approach to study change in the nomological network over time, or a mixed-methods approach that uses both qualitative and quantitative research methods in the same research study to gain deeper insights of BDAC impacts on FPER as well as the mediating effects of BDA-dependent organizational agility and BDA-enabled SBVAL on this relationship (Maughan *et al.* 2015). Secondly, the data used in the study were collected only in the U.S. thus offering insights from a single country. Future studies could collect data from various countries and integrate cultural dimensions into the model. Thirdly, unobserved heterogeneity, a major validity threat to structural equation models was not assessed in this study (Becker *et al.* 2013). Future research should consider this issue, particularly during the data collection and analysis stages. Other opportunities for research could be found in the study of BDA capabilities at the supply chain level.

6. CONCLUSION

This study explored the impact of big data analytics capabilities on strategic business value creation and firm performance. We drew from the literature on IT-dependent organizational agility and the emerging literature on big data analytics to develop a nomological network that integrates different literatures into the big data analytics environment.

Our results contribute to the information systems and big data analytics literature by highlighting the importance of both talent management in developing big data analytics capabilities and the role played by organizational agility in transforming big data insights into business value and improved firm performance. These findings underscore the need for the continual alignment of internal capabilities, business processes and strategy to create value in today's digital, data-rich world and they provide managers with a guide to improve the chances of success of their big data analytics investments.

REFERENCES

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

Baesens, B., Bapna, R., Marsden, J. R., Vanthienen, J., and Zhao, J. L. 2014. "Transformational issues of big data and analytics in networked business," *MIS Quarterly* (38:2), pp. 629-631.

Barbierato, E., Gribaudo, M., and Iacono, M. 2014. "Performance evaluation of NoSQL big-data applications using multi-formalism models," *Future Generation Computer Systems* (37), pp. 345-353.

Barnaghi, P., Sheth, A., and Henson, C. 2013. "From data to actionable knowledge: big data challenges in the web of things," *IEEE Intelligent Systems* (6), pp. 6-11.

Barney, J. B. 1991. "Firm resources and sustained competitive advantage," *Journal of Management* (17), pp. 99-120.

Barton, D., and Court, D. 2012. "Making advanced analytics work for you," *Harvard Business Review* (90:10), p. 78.

Becker, J.-M., Klein, K., and Wetzels, M. 2012. "Hierarchical latent variable models in PLS-SEM: guidelines for using reflective-formative type models," *Long Range Planning* (45:5), pp. 359-394.

Becker, J.-M., Rai, A., Ringle, C. M., and Völckner, F. 2013. "Discovering unobserved heterogeneity in structural equation models to avert validity threats," *MIS Quarterly* (37:3), pp. 665-694.

Becker, J., Beverungen, D. F., and Knackstedt, R. 2010. "The challenge of conceptual modeling for product-service systems: status-quo and perspectives for reference models and modeling languages," *Information Systems and E-Business Management* (8:1) Jan, pp. 33-66.

Bharadwaj, A. 2000. "A resource-based perspective on information capability and firm performance: an empirical investigation," *MIS Quarterly* (24), pp. 169-196.

Braun, V., and Clarke, V. 2006. "Using Thematic Analysis in Psychology," *Qualitative Research in Psychology*, 3, pp. 77-101.

Chae, H.-C., Koh, C. E., and Prybutok, V. R. 2014. "Information technology capability and firm performance: contradictory findings and their possible causes," *MIS Quarterly* (38:1), pp. 305-326.

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

Chen, Y., Wang, Y., Nevo, S., Jin, J., Wang, L., and 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), pp. 326-342.

Chiang, R. H. L., Grover, V., Ting-Peng, L., and Dongsong, Z. 2018. "Special Issue: Strategic Value of Big Data and Business Analytics," *Journal of Management Information Systems* (35:2), pp. 383-387.

Chin, W. W. 1998a. "Commentary: Issues and opinion on structural equation modeling," *MIS Quarterly* (22:1) March 1998, pp. vii-xvi.

Chin, W. W. 1998b. "The partial least squares approach for structural equation modeling," in *Modern methods for business research,* G. Marcoulides (ed.), Psychology Press: New York, pp. 295-336.

Chin, W. W. 2010. "How to write up and report PLS analyses," in *Handbook of partial least squares,* V. Esposito Vinzi, W. W. Chin, J. Henseler and H. Wang (eds.), Springer: Berlin, Heidelberg, pp. 655-690.

Cohen, J. 1988. *Statistical power analysis for the behavioral sciences*, Routledge Academic.

Columbus, L. 2014. "Making Analytics Accountable: 56% Of Executives Expect Analytics to Contribute To 10% Or More Growth in 2014," in *Forbes*. https://www.forbes.com/sites/louiscolumbus/2014/12/10/making-analytics-accountable-56-of-executives-expect-analytics-to-contribute-to-10-or-more-growth-in-2014/

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

Davenport, T. H., and Harris, J. G. 2007a. *Competing on analytics: the new science of winning*, Harvard Business School Press.

Davenport, T. H., and Harris, J. G. 2007b. "The dark side of customer analytics," *Harvard Business Review* (85:5) May, p. 37.

De Swert, K. 2012. "Calculating inter-coder reliability in media content analysis using Krippendorff's Alpha," *Center for Politics and Communication*), pp. 1-15.

Efron, B., and Tibshirani, R. 1993. *An introduction to the bootstrap*, Chapman & Hall/CRC.

Falk, R. F., and Miller, N. B. 1992. *A primer for soft modeling*, University of Akron Press.

Felipe, C. M., Roldán, J. L., and Leal-Rodríguez, A. L. 2016. "An explanatory and predictive model for organizational agility," *Journal of Business Research* (69:10), pp. 4624-4631.

Fink, L., and Neumann, S. 2007. "Gaining agility through IT personnel capabilities: The mediating role of IT infrastructure capabilities," *Journal of the Association for Information Systems* (8:8), pp. 440-462.

Fornell, C., and Larcker, D. F. 1981. "Evaluating structural equation models with unobservable variables and measurement error," *Journal of Marketing Research* (18:1), pp. 39-50.

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

Galliers, R. D. 2007. "Strategizing for Agility: Confronting Information Systems Inflexibility," *Agile Information Systems*), p. 1.

Gandomi, A., and Haider, M. 2015. "Beyond the hype: Big data concepts, methods, and analytics," *International Journal of Information Management* (35:2), pp. 137-144.

Geisser, S. 1975. "The predictive sample reuse method with applications," *Journal of the American Statistical Association* (70:350), pp. 320-328.

George, G., Haas, M., and Pentland, A. 2014. "From the editors: big data and management," *Academy of Management Journal* (57:2), pp. 321-326.

Ghasemaghaei, M., Ebrahimi, S., and Hassanein, K. 2018. "Data analytics competency for improving firm decision-making performance," *The Journal of Strategic Information Systems* (27:1), pp. 101-113.

Grant, R. M. 1991. "The resource-based theory of competitive advantage: implications for strategy formulation," *California Management Review* (33:3), pp. 114-135.

Gregor, S., Martin, M., Fernandez, W., Stern, S., and Vitale, M. 2006. "The transformational dimension in the realization of business value from information technology," *The Journal of Strategic Information Systems* (15:3), pp. 249-270.

Grover, V., Chiang, R. H. L., Ting-Peng, L., and Dongsong, Z. 2018. "Creating Strategic Business Value from Big Data Analytics: A Research Framework," *Journal of Management Information Systems* (35:2), pp. 388-423.

Günther, W. A., Mehrizi, M. H. R., Huysman, M., and Feldberg, F. 2017. "Debating big data: A literature review on realizing value from big data," *The Journal of Strategic Information Systems* (26:3), pp. 191-209.

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

Hair, J. F., Hult, G. T. M., Ringle, C. M., and Sarstedt, M. S. 2017. *A primer on partial least squares structural equation modeling (PLS-SEM)*, Sage Publications: Thousand Oaks, California.

Hair, J. F., Ringle, C. M., and Sarstedt, M. 2011. "PLS-SEM: Indeed a Silver Bullet," *Journal of Marketing Theory and Practice* (19:2), pp. 139-152.

Hayes, A. F. 2011. "My macros and code for SPSS and SAS." http://afhayes.com/spss-sas-and-r-macros-and-code.html

Hayes, A. F., and Krippendorff, K. 2007. "Answering the call for a standard reliability measure for coding data," *Communication methods and measures* (1:1), pp. 77-89.

Hayes, A. F., Preacher, K. J., and Myers, T. A. 2011. "Mediation and the estimation of indirect effects in political communication research," in *Sourcebook for political communication research: Methods, measures, and analytical techniques,* E. P. Bucy and R. L. Holbert (eds.), Routledge: New York, pp. 434-465.

Henke, N., Bughin, J., Chui, M., Manyika, J., Saleh, T., Wiseman, B., and Sethupathy, G. 2016. "The age of analytics: Competing in a data-driven world," McKinsey Global Institute, p. 136.

Hitt, M. A., Xu, K., and Carnes, C. M. 2016. "Resource based theory in operations management research," *Journal of Operations Management* (41:1), pp. 77-94.

Hollands, R. G. 2008. "Will the real smart city please stand up?," *City* (12:3), pp. 303-320.

Holsapple, C. W., and Wu, J. 2009. "A Resource-Based Perspective on Information Technology, Knowledge Management, and Firm Performance," in *Handbook of Research on Contemporary Theoretical Models in Information Systems,* K. D. Yogesh, L. Banita, D. W. Michael, L. S. Scott and W. Michael (eds.), IGI Global: Hershey, PA, USA, pp. 296-310.

Kearns, G. S., and Lederer, A. L. 2003. "A Resource-Based View of Strategic IT Alignment: How Knowledge Sharing Creates Competitive Advantage," *Decision Sciences* (34:1), pp. 1-29.

Kim, G.-H., Trimi, S., and Chung, J.-H. 2014. "Big-data applications in the government sector," *Communications of the ACM* (57:3), pp. 78-85.

Kim, G., Shin, B., Kim, K. K., and Lee, H. G. 2011. "IT capabilities, process-oriented dynamic capabilities, and firm financial performance," *Journal of the Association for Information Systems* (12:7), p. 487.

Kim, G., Shin, B., and Kwon, O. 2012. "Investigating the Value of Sociomaterialism in Conceptualizing

IT Capability of a Firm," *Journal of Management Information Systems* (29:3), pp. 327-362.

Kiron, D. 2013. "Organizational alignment is key to big data success," *MIT Sloan Management Review* (54:3), pp. 1-6.

Kiron, D., Prentice, P. K., and Ferguson, R. B. 2014. "The analytics mandate," *MIT Sloan Management Review* (55:4), pp. 1-25.

Kohli, R., and Grover, V. 2008. "Business Value of IT: An Essay on Expanding Research Directions to Keep up with the Times," *Journal of the Association for Information Systems* (9:1), pp. 23-39.

Krippendorff, K. 2004. "Reliability in content analysis," *Human Communication Research* (30:3), pp. 411-433.

Krippendorff, K. 2007. "Computing Krippendorff's alpha reliability," Departmental Papers (ASC), University of Pennsylvania, http://repository.upenn.edu/asc_papers/43

Lavalle, S., Lesser, E., Shockley, R., Hopkins, M. S., and Kruschwitz, N. 2011. "Big Data, Analytics and the Path From Insights to Value," *MIT Sloan Management Review* (52:2), pp. 21-32.

Lin, Y., and 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), pp. 407-413.

Lindell, M. K., and Whitney, D. J. 2001. "Accounting for common method variance in cross-sectional research designs," *Journal of Applied Psychology* (86:1), p. 114.

Lowry, P. B., and Wilson, D. 2016. "Creating agile organizations through IT: The influence of internal IT service perceptions on IT service quality and IT agility," *The Journal of Strategic Information Systems* (25:3), pp. 211-226.

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

Malhotra, N. K., Kim, S. S., and Patil, A. 2006. "Common method variance in IS research: A comparison of alternative approaches and a reanalysis of past research," *Management Science* (52:12), pp. 1865-1883.

Marr, B. 2018. "Where Big Data Projects Fail," in *Forbes*. https://www.forbes.com/sites/bernardmarr/2015/03/17/where-big-data-projects-fail/#25d487a9239f

Maughan, T., and Young, L. 2015. "Media Network: Three Moments from the Future Post-Manufacturing Supply Chain," *Architectural Design* (85:4), pp. 88-93.

McAfee, A., and Brynjolfsson, E. 2012. "Big Data: The Management Revolution," *Harvard Business Review* (90:10), pp. 60-68.

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

Mooney, J. G., Gurbaxani, V., and Kraemer, K. 1996. "A process oriented framework for assessing the business value of information technology," *The Data Base for Advances in Information Systems* (27), pp. 68-81.

Müller, O., Fay, M., and Vom Brocke, J. A. N. 2018. "The Effect of Big Data and Analytics on Firm Performance: An Econometric Analysis Considering Industry Characteristics," *Journal of Management Information Systems* (35:2), pp. 488-509.

Newbert, S. L. 2007. "Empirical research on the resource-based view of the firm: an assessment and suggestions for future research," *Strategic Management Journal* (28:2), pp. 121-146.

Opresnik, D., and Taisch, M. 2015. "The value of Big Data in servitization," *International Journal of Production Economics* (165), pp. 174-184.

Orlikowski, W. J. 2007. "Sociomaterial Practices: Exploring Technology at Work," *Organization Studies* (28:9), pp. 1435-1448.

Orlikowski, W. J., and Scott, S. V. 2008. "Sociomateriality: Challenging the Separation of Technology, Work and Organization," *The Academy of Management Annals* (2:1), pp. 433-474.

Partners, N. 2019. "Big Data and AI Executive Survey 2019," NewVantage Partners LLC. https://newvantage.com/wp-content/uploads/2018/12/Big-Data-Executive-Survey-2019-Findings-Updated-010219-1.pdf

Phillips-Wren, G., Iyer, L. S., Kulkarni, U., and Ariyachandra, T. 2015. "Business Analytics in the Context of Big Data: A Roadmap for Research," *Communications of the Association for Information Systems* (37:1), p. 23.

Podsakoff, P. M., and Organ, D. W. 1986. "Self-reports in organizational research: Problems and prospects," *Journal of Management* (12:4), pp. 531-544.

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

Raschke, R. L. 2010. "Process-based view of agility: The value contribution of IT and the effects on process outcomes," *International Journal of Accounting Information Systems* (11:4), pp. 297-313.

Ringle, C. M., Wende, S., and Becker, J.-M. 2014. "SmartPLS 3," SmartPLS GmbH: Boenningstedt.

Ross, J. W., Beath, C. M., and Quaadgras, A. 2013. "You may not need big data after all," *Harvard Business Review* (91:12), pp. 90-98.

Santhanam, R., and Hartono, E. 2003. "Issues in linking information technology capability to firm performance," *MIS Quarterly* (27:1), pp. 125-153.

Shekhar, S., Gunturi, V., Evans, M. R., and Yang, K. 2012. "Spatial big-data challenges intersecting mobility and cloud computing," Proceedings of the Eleventh ACM International Workshop on Data Engineering for Wireless and Mobile Access, ACM2012, pp. 1-6.

Srivastava, R. K., Fahey, L., and Christensen, H. K. 2001. "The resource-based view and marketing: The role of market-based assets in gaining competitive advantage," *Journal of Management* (27:6), pp. 777-802.

Stanko, M. A., Molina-Castillo, F. J., and Munuera-Aleman, J. L. 2012. "Speed to market for innovative products: blessing or curse?," *Journal of Product Innovation Management* (29:5), pp. 751-765.

Stone, M. 1974. "Cross-validatory choice and assessment of statistical predictions," *Journal of the Royal Statistical Society. Series B (Methodological)*), pp. 111-147.

Swafford, P. M., Ghosh, S., and Murthy, N. N. 2006. "A framework for assessing value chain agility," *International Journal of Operations & Production Management* (26:2), pp. 118-140.

Tallon, P. P., and 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), pp. 463-486.

Taylor, P. 2012. "Crunch time for big data," in *Financial Times*, FT Group: London.

Tenenhaus, M., Vinzi, V. E., Chatelin, Y.-M., and Lauro, C. 2005. "PLS path modeling," *Computational statistics & data analysis* (48:1), pp. 159-205.

Tippins, M. J., and Sohi, R. S. 2003. "IT competency and firm performance: is organizational learning a missing link?," *Strategic Management Journal* (24:8), pp. 745-761.

Verbraken, T., Lessmann, S., and Baesens B. Year. "Toward Profit-Driven Churn Modeling with Predictive Marketing Analytics," Proceedings of the 11th Workshop on e-Business (WEB'2012), Orlando, FL, USA, 2012.

Vitari, C., and Raguseo, E. 2016. "Digital data, dynamic capability and financial performance: an empirical investigation in the era of Big Data," *Systèmes d'Information et Management* (21:3), pp. 63-92.

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

Wernerfelt, B. 1984. "A resource based view of the firm," *Strategic Management Journal* (5:2), pp. 171-180.

Wetzels, M., Odekerken-Schroder, G., and Van Oppen, C. 2009. "Using PLS path modeling for assessing hierarchical construct models: guidelines and empirical illustration," *MIS Quarterly* (33:1), p. 177.

Wixom, B. H., Yen, B., and Relich, M. 2013. "Maximizing value from business analytics," *MIS Quarterly Executive* (12:2), pp. 111-123.

Wu, J., Li, H., Cheng, S., and Lin, Z. 2016. "The promising future of healthcare services: When big data analytics meets wearable technology," *Information & Management* (53:8), pp. 1020-1033.

Yang, C., and Liu, H.-M. 2012. "Boosting firm performance via enterprise agility and network structure," *Management Decision* (50:6) 2012, pp. 1022-1044.

APPENDIX

2nd-order constructs	Type	1st-order constructs	Type	Item labels	Items	Sources
BDA management capability	Molecular	Planning	Reflective	BPLAN1	We continuously examine the innovative opportunities for the strategic use of big data analytics	Akter *et al.* (2016)
			Reflective	BPLAN2	We enforce adequate plans for the introduction and utilization of big data analytics.	
			Reflective	BPLAN3	We perform big data analytics planning processes in systematic and formalized ways.	
			Reflective	BPLAN4	We frequently adjust big data analytics plans to better adapt to changing conditions.	
		Investment decision-making	Reflective	BIDMK1	When we make big data analytics investment decisions, we think about and estimate the effect they will have on the productivity of the employees' work.	
			Reflective	BIDMK2	When we make big data analytics investment decisions, we consider and project about how much these options will help end-users make quicker decisions.	
			Reflective	BIDMK3	When we make big data analytics investment decisions, we think about and estimate the cost of training that end-users will need.	
			Reflective	BIDMK4	When we make big data analytics investment decisions, we consider and estimate the time managers will need to spend overseeing the change.	
		Coordination	Reflective	BCORD1	In our organization, big data analysts and line people meet frequently to discuss important issues both formally and informally.	
			Reflective	BCORD2	In our organization, big data analysts and line people from various departments frequently attend cross-functional meetings.	
			Reflective	BCORD3	In our organization, big data analysts and line people coordinate their efforts harmoniously.	
			Reflective	BCORD4	In our organization, information is widely shared between big data analysts and line people so that those who make decisions or perform jobs have access to all available know-how.	
		Control	Reflective	BCONT1	In our organization, the responsibility for big data analytics development is clear.	
			Reflective	BCONT2	We are confident that big data analytics project proposals are properly appraised.	
			Reflective	BCONT3	We constantly monitor the performance of the big data analytics function.	
			Reflective	BCONT4	Our big data analytics department is clear about its performance criteria.	

BDA infrastructure capability	Molecular	Connectivity	Reflective	BCONN1	Compared to rivals within our industry, our organization has the foremost available big data analytics systems.	Akter *et al.* (2016)
			Reflective	BCONN2	All remote, branch, and mobile offices are connected to the central office for big data analytics.	
			Reflective	BCONN3	Our organization utilizes open systems network mechanisms to boost big data analytics connectivity.	
			Reflective	BCONN4	There are no identifiable communications bottlenecks within our organization when sharing big data analytics insights.	
		Compatibility	Reflective	BCOMP1	Software applications can be easily transported and used across multiple big data analytics platforms.	
			Reflective	BCOMP2	Our user interfaces provide transparent access to all platforms and applications.	
			Reflective	BCOMP3	Big data analytics-driven information is shared seamlessly across our organization, regardless of the location.	
			Reflective	BCOMP4	Our organization provides multiple big data analytics interfaces or entry points for external end-users.	
		Modularity	Reflective	BMODU1	Reusable software modules are widely used in new big data analytics model development.	
			Reflective	BMODU2	End-users utilize object-oriented tools to create their own big data analytics applications.	
			Reflective	BMODU3	Object-oriented technologies are utilized to minimize the development time for new big data analytics applications.	
			Reflective	BMODU4	Applications can be adapted to meet a variety of needs during big data analytics tasks.	

BDA personnel capability	Molecular	Technical Knowledge	Reflective	BTKNO1	Our big data analytics personnel are very capable in terms of programming skills.	Akter *et al.* (2016)
			Reflective	BTKNO2	Our big data analytics personnel are very capable in terms of managing project life cycles.	
			Reflective	BTKNO3	Our big data analytics personnel are very capable in the areas of data and network management and maintenance.	
			Reflective	BTKNO4	Our big data analytics personnel create very capable decision support systems.	
		Technology Management Knowledge	Reflective	BTMGM1	Our big data analytics personnel show superior understanding of technological trends.	Akter *et al.* (2016)
			Reflective	BTMGM2	Our big data analytics personnel show superior ability to learn new technologies.	
			Reflective	BTMGM3	Our big data analytics personnel are very knowledgeable about the critical factors for the success of our organization.	
			Reflective	BTMGM4	Our big data analytics personnel are very knowledgeable about the role of big data analytics as a means, not an end.	
		Business Knowledge	Reflective	BBUKN1	Our big data analytics personnel understand our organization's policies and plans at a very high level.	Akter *et al.* (2016)
			Reflective	BBUKN2	Our big data analytics personnel are very capable in interpreting business problems and developing appropriate technical solutions.	
			Reflective	BBUKN3	Our big data analytics personnel are very knowledgeable about business functions.	
			Reflective	BBUKN4	Our big data analytics personnel are very knowledgeable about the business environment.	
		Relational Knowledge	Reflective	BREKN1	Our big data analytics personnel are very capable in terms of planning, organizing, and leading projects.	Akter *et al.* (2016)
			Reflective	BREKN2	Our big data analytics personnel are very capable in terms of planning and executing work in a collective environment.	
			Reflective	BREKN3	Our big data analytics personnel are very capable in terms of teaching others.	
			Reflective	BREKN4	Our big data analytics personnel work closely with customers and maintain productive user/client relationships.	

Big data dependent organizational agility	Molecular	System agility	Reflective	SYAGL1	Big data analytics shared across the company saves money by reducing business analytics system modification or enhancement costs	Fink and Neumann (2007)
			Reflective	SYAGL2	Big data analytics shared across the company allows other business analytics applications to be developed faster	
			Reflective	SYAGL3	Big data analytics shared across the company allows previously infeasible business analytics applications to be implemented	
			Reflective	SYAGL4	Big data analytics shared across the company provides the ability to perform business analytics maintenance faster	
		Information agility	Reflective	INAGL1	Big data analytics shared across the company enables faster retrieval or delivery of information or reports	
			Reflective	INAGL2	Big data analytics shared across the company enables easier access to information	
			Reflective	INAGL3	Big data analytics shared across the company presents information in a more concise manner or better format	
			Reflective	INAGL4	Big data analytics shared across the company increases the flexibility of information requests	
		Strategic agility	Reflective	STAGL1	Big data analytics shared across the company enhances competitiveness or creates strategic advantage	
			Reflective	STAGL2	Big data analytics shared across the company enables the company to catch up with competitors	
			Reflective	STAGL3	Big data analytics shared across the company helps establish useful linkages with other organizations	
			Reflective	STAGL4	Big data analytics shared across the company enables the company to respond more quickly to change	
Strategic business value	NA	NA	Reflective	Big data analytics ____:		Gregor *et al.* (2006)
				SBVAL1	Enables quicker response to change	
				SBVAL2	Improves customer relations	
				SBVAL3	Provides better products or services to customers	
Firm performance	NA	NA	Reflective	Using big data analytics ____:		Tippins and Sohi (2003)
				FPER1	We have gained strategic advantages over our competitors.	
				FPER2	We have a large market share.	
				FPER3	Overall, we are more successful than our major competitors.	