Big data-savvy teams' skills, big data-driven actions and business performance

Pervaiz Akhtar[a] , Jędrzej George Frynas[b], Kamel Mellahi[c], Subhan Ullah[d]

[a] Management Systems, Logistics Institute, Faculty of Business, Law and Politics, University of Hull; IESEG School of Management, France; Abasyn University, Pakistan
[b] Open University
[c] Warwick Business School, University of Warwick
[d] Accounting and Finance, Faculty of Business, Law and Politics, University of Hull

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Abstract:

Prior studies on big data analytics have emphasized the importance of specific big data skills and capabilities for organizational success; however, they have largely neglected to investigate the use of cross-functional teams' skills and its links to the role played by relevant data-driven actions and business performance. Drawing on the resource-based view (RBV) of the firm and on the data collected from big data experts working in global agrifood networks, we examine the links between the use of big data-savvy (BDS) teams' skills, big data-driven (BDD) actions and business performance. BDS teams depend on multidisciplinary skills (e.g., computing, mathematics, statistics, machine learning, and business domain knowledge) that help them to turn their traditional business operations into modern data-driven insights (e.g., knowing real time price changes and customer preferences), leading to BDD actions that enhance business performance. Our results, raised from structural equation modelling, indicate that BDS teams' skills that produce valuable insights are the key determinants for BDD actions, which ultimately contribute to business performance. We further demonstrate that those organisations that emphasise BDD actions perform better compared to those that do not focus on such applications and relevant insights.

Keywords: Big data-savvy teams; big data multidisciplinary skills; big data-driven actions; resource-based view; business performance

Introduction

Organisations must have the capabilities suited to successfully use and benefit from large structured (e.g., those drawn from financial records and stock exchanges) and unstructured datasets (e.g., those generated by emails, tweets, and GPS signals)—i.e., big data. We define such big data capabilities as an effective combination of relevant human resources, prerequisite big data skills (both functional and team-based), advanced technologies, mathematical and statistical techniques, and machine learning tools that produce and process large datasets to generate analytical reports and actionable insights utilised for improving performance (cf. (Barton and Court, 2012; Davenport and Patil, 2012; Schoenherr and Speier-Pero, 2015). The characteristics of big data (e.g., definition, volume, variety, velocity, and complexity) and the usefulness of big data analytics are well documented in the literature (Sheng, Amankwah-Amoah and Wang, 2017; Davenport and Patil, 2012; Tambe, 2014; Cohen et al., 2009). However, little is known about the links between the use of big data skills in multi-disciplinary teams, big data-driven (BDD) actions and business performance—a gap that this article aims to fill.

Reportedly, those organisations that can integrate big data analytics into their operations have higher productivity and better financial performance compared to those that do not (e.g. Barton and Court, 2012; Brynjolfsson, Hitt and Kim, 2011). One study found that retailers can achieve increases of up to 15-20% in their return on investment by effectively exploiting big data applications or using BDD actions (Wamba et al., 2015); this can help to explain the significant growth in the demand for skills related to big data analytics (Sheng et al., 2017). For instance, it has been predicted that, by 2018, the US alone may require 140,000 to 190,000 people with advanced data and analytical skills (e.g., statistical and machine learning techniques), and the demand for such skills is also considerable in other developed countries (Brown, Chui and Manyika, 2011). To meet such demand, data and analytical team managers (e.g., data scientists) have been included in skill shortage lists (UK-Immigration, 2017), while many universities have also increased their offering of data and analytical programmes (Schoenherr and Speier-Pero, 2015).

Big data analytics also require the expensive organizational resources (e.g., technology and skilled big data-savvy teams) that play a key role in extracting the insights that contribute to business performance (Brynjolfsson et al., 2011; Provost and Fawcett, 2013; Real, Roldán and Leal, 2014). Analysing big data requires skills drawn from different fields—including operations management, computing, mathematics, and statistics—and it is thus imperative to build big data-savvy (BDS) teams equipped with skill portfolios drawn from multidisciplinary domains, so that effective insights for better business performance can be obtained (Akhtar et al., 2018; Davenport and Patil, 2012; Sheng et al., 2017). For example, BDS teams at Wal-Mart applied their skills to effectively manage inventories in the wake of recent hurricanes in the US; this helped to increase profit and maintain customer satisfaction, which are key aspects of their business performance. Similarly, MegaTelCo's multidisciplinary team used big data to decide which key customers should be offered incentives; this helped the company to retain key customers and to increase their satisfaction (Provost and Fawcett, 2013). The multidisciplinary team of data-savvy scientists at Aridhia (one of the world's leading organisations in clinical informatics) has also been incorporating Hadoop, Structured Query Language, and Memory Data to build a centralized data system suited to enable them to provide personalized treatment options (Roche, 2017).

Unfortunately, our understanding of the linkages between the use of BDS teams' skills and business performance is severely limited. Studies from different domains such as information technology (Katal, Wazid and Goudar, 2013; LaValle et al., 2011; Liben-Nowell and Kleinberg, 2007), information management and business intelligence (Chen, Chiang and Storey, 2012), machine learning (Lantz, 2015; Wu et al., 2008), and operations management

(Schoenherr and Speier-Pero, 2015; Tan et al., 2015; Davenport and Patil, 2012; Tambe, 2014) have emphasized the importance of specific big data skills and capabilities for organizational success. For instance, those researchers highlighted the benefits of the effective use of Hadoop technology (Tambe, 2014), text mining (Liben-Nowell and Kleinberg, 2007), algorithms, and statistical techniques (Wu et al., 2008) for business success. However, studies and consultancy reports are providing anecdotal evidence that success in exploiting big data may not lie merely with unique technical skills and capabilities, but that the formation of cross-functional teams may also be crucial for the success of big data projects and business performance; this implies that the relevant projects and their related performance outcomes require interdisciplinary cooperation between various people applying their diverse skills to drawing insights out of big data (Dutta and Bose, 2015; Akhtar et al., 2018; Davenport and Patil, 2012; Wamba et al., 2015; Sheng et al., 2017). This line of reasoning is supported by insights drawn from the resource-based view (RBV), the dynamic capabilities (DC) lens, and human capital theory (HCT), which tells us that what matters is not a disparate managerial resource, but how and which bundles of skills and the relevant knowledge domains of individuals are applied by BDS teams to contribute to business performance. However, to our knowledge, no previous study has investigated how the make-up and applications of big data skills within cross-functional teams (the BDS teams that produce valuable insights for taking actions) influence BDD actions and business performance.

Consequently, this study contributes to the emerging extant literature by developing a framework and investigating the relationships between the use of BDS teams' skills grounded in the RBV, BDD actions, and business performance. Business performance is measured through four dimensions: 1) environmental performance, 2) operational performance, 3) business development, and 4) financial performance. Specifically, in order to explain the drivers of business performance, this study employs empirical data collected from 240 relevant experts on team level big data skills. The framework focuses on the specific applications of BDS teams' skills (e.g., text mining, image processing, programming, machine learning, and large volume of data handling) that help to gain insights suited to the enactment of data-driven actions (e.g., identifying business performance gaps, identifying customer buying-selling patterns, making effective decisions, taking actions suited to improve service quality, making effective investment decisions, and taking actions against competitors), thus leading to enhanced business performance (i.e., the four dimensions mentioned above). It also demonstrates how the joint use of BDS teams' skills and BDD actions drive better business performance (i.e., have a mediating effect on business performance).

Our article is structured as follows. The next section presents the theoretical background for the hypotheses, and is followed by a methodology section. Subsequently, the results of the study are discussed. Finally, the paper concludes by outlining the theoretical and practical implications.

Theoretical background and framework

Linkages between the use of BDS teams' skills, BDD actions, and business performance

The core thesis of the RBV is that organizational resources and management competencies play a crucial role in improving organizational performance (e.g., Barney, 1991; Peteraf, 1993; Crook, Ketchen, Combs and Todd, 2008; Kraaijenbrink, Spender and Groen, 2010). Drawing on the RBV of the firm, we examine the links between the bundling of key big data resources and capabilities—namely, the use of multi-skilled teams' skills and relevant data-driven actions—and organizational performance. The question of how talent drawn from different disciplines is bundled together to achieve a competitive advantage is well established (Collings, Mellahi and Cascio, 2017). Indeed, a large body of research has drawn on RBV to demonstrate that the bundling of internal resources is associated with improved performance (Barney and

Arikan, 2001; Sirmon, Hitt, Ireland and Gilbert, 2011; Kraaijenbrink et al., 2010). In regard to this study, RBV research specifically demonstrates that the skilful bundling of information technology resources—specifically, big data-related resources (Wamba et al., 2015; Tan et al., 2015; Wamba et al., 2017; Wang and Hajli, 2017)—increases organizational performance (Malhotra et al., 2006; (Aral and Weill, 2007; Nevo and Wade, 2010; Fawcett et al., 2011).

While RBV scholarship—including recent studies on the RBV of information technology—tends to focus on functional capabilities (e.g., technical or marketing capabilities), there is support for the link between multi-functional resources and skills and competitive advantage (Nath, Nachiappan and Ramanathan, 2010). A parallel body of research has revealed that the integration of knowledge drawn from multi-disciplinary teams leads to higher innovation performance (Gibson, Waller, Carpenter and Conte, 2007; Pearce and Ensley, 2004; Van Der Vegt and Bunderson, 2005). A study of the performance of multi-disciplinary teams in the movie industry argued and demonstrated support for the link between competitive advantage and the use of multi-disciplinary teams (Miller and Shamsie, 1996). The study argued that "*it is not the skills in any one domain, but rather, the way skills from several domains complement one another in teams that provide many organisations their competitive advantage*". This is because nurturing a culture of collaboration between—and developing routines around—multi-disciplinary teams is a capability that competitors cannot easily imitate. Therefore, the authors concluded that those organisations that are adept at integrating and coordinating talent drawn from different disciplines are likely to achieve a competitive advantage (Miller and Shamsie, 1996). The core argument here is that organisations capable of deploying and coordinating their different resources achieve two objectives. First, superior performance resulting from the collective learning and pooling of knowledge, especially in complex tasks. Second, competencies related to fostering knowledge sharing and integration (e.g., specific skills in managing and applying big data) that are difficult to imitate by competitors because they are context specific. Multi-skilled BDS teams that utilise such skills gain insights from complex data and take more effective BDD actions that result in increased performance (Akhtar et al., 2018; Sheng et al., 2017).

Big data analytics provides useful insights that can be utilised to take relevant actions; these include the detection of buying patterns and the setting up of shop floors, making decisions for automotive inventory management, and the segmentation of customers based on their social site and location data characteristics (APICS, 2012). The production of insights and subsequent decision-making based upon big data are BDD actions—the latter of which contributes to business performance (Chen et al., 2012; Katal et al., 2013; Schoenherr and Speier-Pero, 2015). Organizations utilise big data related resources—such as BDS teams' skills—to predict business performance indicators such as sales and profits. For instance, decision trees are used to identify those customers who are likely to discontinue using products or services, ultimately affecting sales and profits; this helps firms to take relevant actions. Similarly, basket analysis is used in retail stores to detect combinations of products that are regularly bought by customers. These valuable insights, based on big data analytics, enable organisations to take actions in regard to laying out products in ways that induce customers to buy related ones together. This not only increases company sales but also contributes to customer satisfaction, relationship management, and loyalty, thus jointly contributing to business performance (Anderson, Jolly and Fairhurst, 2007; Lantz, 2015; Erevelles, Fukawa and Swayne, 2016). Overall, there is strong evidence to suggest that analytical applications and business domain knowledge produce insights that lead organizations to take relevant BDD actions, subsequently improving their performance (Chen and Zhang, 2014; Akhtar et al., 2018; Sheng et al., 2017; Dutta and Bose, 2015).

Our thesis is that, given the nature and diverse skills needed to analyse big data (Bizer, Boncz, Brodie and Erling, 2012; Tambe, 2014; Akhtar et al., 2018), the value created through big data analytics is optimised when diverse skills are used and the knowledge pooled from different sources is acted upon. The leveraging of such capability requires big data experts with specialized skills to work together and contribute both independently and collectively to take effective actions. Empirical work and anecdotal evidence suggest that BDS teams need to utilize diverse expertise in order to effectively capitalize on the advantages provided by big data. Researchers (e.g., Barton and Court, 2012; Davenport and Patil, 2012; Schoenherr and Speier-Pero, 2015; Sheng et al., 2017) have advocated that BDS teams need relevant knowledge and reasonable technical skills in multiple domains such as information management and business intelligence (Chen et al., 2012), machine learning (Lantz, 2015; Wu et al., 2008), statistics, mathematics, computing, and operations research (Schoenherr and Speier-Pero, 2015; Tan et al., 2015; Davenport and Patil, 2012; Tambe, 2014; Cohen et al., 2009). However, BDS team members do not need to be hard-core mathematicians, statisticians, or computer scientists, as some of the best BDS team experts also come from ecology, systems biology, operations management, and general business domains (Davenport and Patil, 2012). To analyse big data and enhance business performance, BDS teams may use diverse data mining skills and techniques—such as classification, clustering, regression, association, and neuro network analyses (Chen et al., 2012)—that require varied disciplinary skills. Such skills and techniques are based on a number of popular algorithms—including C4.5, K-means, support vector machine, Apriori, expectation maximization, PageRank, AdaBoost, K-nearest neighbours, Naive Bayes, and CART (Wu et al., 2008)—which are unlikely to be all known by one person. Furthermore, other related but different sets of skills such as statistical machine learning based on various techniques—including Bayesian networks, reinforcement learning, support vector machine, Hidden Markov models, and process mining—are widely used for web analytics, text mining, and supply chain mapping, and detecting operational problems. MapReduce and Hadoop also help BDS teams to access and transfer large-scale datasets simultaneously, which enables them to make timely and effective decisions. Network analytics is also an emerging area in which BDS teams build on and apply their diverse skills, for example, to link-mining (Liben-Nowell and Kleinberg, 2007) and community detection (Fortunato, 2010). In link-mining, BDS teams can predict or uncover links between the existing nodes (e.g., customers, end users, and products) of a firm's business network, links that can potentially contribute to its operational performance. Automated business processes and big data analytics often require skills drawn from very diverse fields, such as inferential statistical (e.g., prediction, causality analysis, and comparisons of buying patterns), computer programming (e.g., R, Matlab, SQL, and MapReduce) and meteorological and mathematical skills needed to produce daily weather analytics and their effects on business operations, among others (Cohen et al., 2009; Brown et al., 2011; Davenport and Patil, 2012). By implication, value can be captured from big data analytics only if multi-skilled team members work together to share, pool, and integrate their diverse knowledge.

The above discussion suggests that, used in isolation, the available techniques can only provide parts of the bigger picture and that a holistic view of a complex and fast moving phenomenon can emerge and effective decisions be made only when all the evidence is pieced together. In addition, the fact that all BDS team members would have provided their interpretation and input at the outset would result in consistent recommendations being passed on to management or relevant action teams. The full potential of BDS teams is optimized when, for instance, techniques drawn from machine learning (e.g., cluster analysis, classification, regression, and association), optimisation (e.g., stochastic and classification optimisation), network analysis (e.g., social network and social media analysis), visualisation methods, spatial data analysis, and signal processing are integrated together, and BDD actions are taken as required to improve business performance. For instance, BDS teams from Wal-Mart and Taobao have successfully used most of these techniques to gain higher competitiveness in real time pricing, advertising, and evidence-based or automated decision making (Chen and Zhang, 2014). Thus, we argue that the use of BDS teams' skills enables organisations to gain the valuable insights that will enable them to take effective actions and also improve their business performance.

In line with the above discussion, the following hypotheses are proposed:

H1: The use of BDS teams' skills is positively related to business performance.

H2: The use of BDS teams' skills is positively related to BDD actions.

The theoretical framework depicted in Figure 1 succinctly shows the interrelationships discussed in the literature. The use of BDS teams' skills in getting insights from big data positively affects business performance and BDD actions, which are ultimately linked with business performance.

[Insert Figure 1 here]

BDD actions, business performance and mediation effects

The RBV suggests that, unless they are complemented by specific managerial actions, resources and skills may not be sufficient to improve organizational performance. While past RBV scholarship has often presumed that the actions required to leverage resources and skills are self-evident (Barney and Arikan, 2001:174), more recent RBV research on 'resource orchestration' has explored in some detail how managerial decision-making and actions impact organizational performance in regard to resource management processes (Helfat and Peteraf, 2015; Sirmon et al., 2011; Sirmon and Hitt, 2009). This research suggests that, while controlling valuable and rare resources is necessary to achieve competitive advantage, managers must take additional actions to exploit and develop such resources, *inter alia* by structuring their organizations' resource portfolios (e.g., by acquiring and letting go of resources), by bundling resources into capabilities (e.g., by enriching any existing capabilities and pioneering new ones), and by leveraging capabilities to create value for customers (e.g. by linking capabilities to new market opportunities and entrepreneurial strategies) (Hitt, Ireland, Sirmon and Trahms, 2011).

Empirical studies on resource orchestration have demonstrated that organizational performance is strongly affected by investment and deployment decisions related, for example, to physical capital resources such as buildings, equipment, information technologies (Sirmon and Hitt, 2009), managerial actions with regards to the acquisition and deployment of knowledge resources such as employees with new experiences and team co-specialization (Lanza, Simone and Bruno, 2016) and human resource flow strategies such as decisions on human resource inflows and human resource outflows (Fainshmidt, Smith and Guldiken, 2017). Likewise, managerial actions related to the deployment of human resources within teams with heterogeneous big data skills could be expected to exploit opportunities and create new options for organizations, and hence lead to improvements in their performance.

With reference to big data applications and relevant actions, consultancy reports and academic studies provide evidence that BDD actions improve organizational performance. For example, one consultancy report showed how investment in collecting, integrating, and analysing data from retail stores and linking the information with large suppliers' databases would enable retailers to reorder hot-selling items automatically, adjusting prices in real time and improving logistics between stores. As a result, information from the floor would instantly be made available to CEOs, which would enable them to make evidence-based or automated decisions, leading to actions that would directly contribute to improved business performance (Brown et al., 2011). A longitudinal case study of Australia's New South Wales State Emergency Service showed that BDD actions had significantly improved its performance. Its BDS teams had integrated structural and unstructured data across agencies with a range of IT capabilities (radio, telephony, spatial systems, and enterprise resource planning—SAP and

Microsoft SharePoint), they had set up bi-directional communication through various communication channels (e.g., corporate website, Twitter, radio, and smart phones) and real-time access through a dashboard, and had further integrated weather data and emergency information. This data and analytics single-point access had enabled the Service to take preventive measures such as advanced alerts, evacuations, and real-time risk management (Wamba et al., 2015). A leading Chinese eyeglass manufacturer, used a similar information management system and various big data techniques and actions (Apach, Mahout, Tableau, Storm, InfoSphere, and deduction graphs) to detect its existing customers' preferences. It used videos, photos, social media information, registration databases, and the shopping histories of six million registered customers to gain insights from its big data. These extracted insights and big data analytics helped them to manufacture innovative products in response to big data recommendations. This intensive-connectivity approach also enabled the company to improve its supply chain operations (Tan et al., 2015).

While the extant research provides growing evidence that managerial decision making processes are important for the implementation of big data projects and that BDD actions lead to organizational performance improvements (Davenport, 2014; Dutta and Bose, 2015; Sheng et al., 2017), the understanding of the specific linkages between big data skills, BDD actions, and performance is very limited. Insights gained through the RBV lens tell us that the role played by managerial decision-making is much greater than that of the simple effective implementation of investments in big data in order to gain cost advantages and other operational improvements. The RBV scholarship has demonstrated that managerial actions must simultaneously address both capability strengths and weaknesses to achieve the competitive advantages suited for an organization to pursue future market opportunities (Sirmon, Hitt, Arregle and Campbell, 2010), that new resource combinations of technological resources can lead to innovations and can support disruptive competitive actions (Galunic and

Rodan, 1998) and, indeed, that the importance of such actions increases as the resource portfolios of business rivals approach competitive parity (Sirmon and Hitt, 2009). Specifically, the RBV scholarship provides robust empirical evidence that managerial actions mediate the relationship between resources/capabilities and performance (Ndofor, Sirmon and He, 2011; Sirmon et al., 2010; Miao, Coombs, Qian and Sirmon, 2017). This mediating relationship may arise, *inter alia,* with respect to the complexity of a firm's competitive behaviour (Ndofor, Sirmon and He, 2011), entrepreneurial orientation (Miao et al., 2017) and, most pertinent for our investigation, intra-team processes (Stewart and Barrick, 2000). Consequently, we hypothesize:

H3: BDD actions are positively related to business performance.

H4: BDD actions mediate the relationship between the use of BDS teams' skills and business performance.

In summary, as shown in Table 1, most of the relevant big data studies are exploratory case based, literature reviews, or theoretical papers proposing theoretical frameworks. This demonstrates that the big data field is still in its infancy. Although, as shown in Table 1, a few survey-based studies exist (Wang and Hajli, 2017; Wamba et al., 2017), these are mainly exploratory and seek to capture perceptions of state of the art practices. Also, their measures (items)/constructs for dependent variables are limited; consequently, they do not measure business performance comprehensively. Additionally, BDS teams' skills and BDD actions have not been incorporated or mediated in previous studies, leaving a gap in the RBV prospective—in particular in the big data RBV. Our study contributes to this knowledge gap and takes its data sample from agrifood networks that are under research in regard to big data. Our theoretical development and testing thus significantly contribute to big data applications and to the prerequisite BDS teams' skills interlinked with BDD actions needed in order to manage contemporary business operations effectively.

Methodology

Sample

The sample for this study consists of selected global agrifood networks (dairy, meat, vegetables, and fruits) headquartered in New Zealand and in European countries—mainly Belgium, France, Germany, Hungary, Ireland, Italy, Poland, Spain, and the UK. The massive import and export operations of these networks are also linked with other countries in Asia, Africa, North America, South America, Antarctica, and Australia—Figure 2 provides more details.

[Insert Figure 2 here]

The main reason for selecting these import and export agrifood networks was the lack of research in this globally connected domain. The selected products/produce not only play a vital role in the global agricultural economy (Akhtar et al., 2018), but present many opportunities for big data applications. Different experts—such as production and operational analysts, IT managers and analysts, big data scientists, and business development analysts—were found as suitable sample respondents from the selected global agrifood networks. A pilot survey was first conducted to verify the suitability of these respondents; this ensured that the selected research participants extensively used big data and also possessed the prerequisite skills. A total of 1050 copies of our survey questionnaire were then sent to these participants. Having excluded the unusable responses, we were able to execute the structural equation modelling of 240 cases. The sample characteristics are listed in Table 2.

[Insert Table 2 here]

Measurement Scales

Few empirical and survey-based studies on big data and performance exist (Wang and Hajli, 2017; Wamba et al., 2017) and there is a lack of items suited to measure our underlying constructs. To the best of our knowledge, to date, no items (questions) have been developed to measure BDS teams' skills and BDD actions.

The scales in our study were developed using a comprehensive procedure suggested by other researchers (e.g., Shah and Ward, 2007; Zhang et al., 2016). The relevant literature from multidisciplinary domains (e.g., Davenport, 2006; Cohen et al., 2009; Chen et al., 2012) and experts (i.e., research participants) guided us to ask the relevant questions suited to develop the underlying constructs. An exploratory factor analysis (EFA) with varimax rotations, eigenvalues ≥ 1, and scree plots statistically refined them. A total of eight items were used to measure the use of BDS teams' skills. These items measured a variety of skills in advanced operational techniques, image-processing for special data, machine learning (e.g., basket analysis and neural network analysis), web analytics, unstructured data mining (e.g., text analysis, reviews, and tweeter mining), and relevant programming skills. The construct, which was related to big data-driven (BDD) actions, measured various actions based on insights obtained from big data analytics. A total of nine items were used: 1) implementing automated-inventory management, 2) reacting as suggested by big data analytics (BDA), 3) targeting customer demand, 4) intervening in existing strategies and taking relevant actions as recommended by BDA, 5) using big data analytics for automated-decision making, 6) taking BDD actions, 7) investing in markets based on BDA, 8) understanding competitor strengths by utilising BDA, and 9) prioritising tasks based upon insights provided by BDA .

The business performance measure consisted of four dimensions: environmental, operational, new business development, and financial. These dimensions were measured using more than 20 items. Although we used EFA to further develop them, these dimensions were taken from well-established studies. Environmental performance was measured in relation to reusable packaging, material efficiency, wastewater reduction, total waste reduction for recycling, overall impacts, and energy consumption (Rao, la O'Castillo, Intal Jr and Sajid, 2006). Operational performance was measured in terms of service quality (on time deliveries, order accuracy, and order flexibility) and product quality (product safety, product defective rates, and product reliability) (Aramyan, Lansink, Van Der Vorst and Van Kooten, 2007). Business development was gauged in relation to both internal organizational and market growth over a total of nine items; i.e., partnering with new businesses; focussing on diversification; proportion of new businesses to total assets; regular investment in new markets; expansion of internal business operations; increases in the revenues of new businesses; expansion of operations in other markets; success of developing businesses in new markets; and the search for new opportunities (LaValle et al., 2011; Li, Wang, Huang and Bai, 2013; Blackburn, Hart and Wainwright, 2013). Additionally, profitability, return on investment, and cash flows represented financial performance (Real et al., 2014; Kyrgidou and Spyropoulou, 2013). All scales used a 5-point Likert scale.

Quality checks

Non-response bias was assessed by computing chi-square difference tests. No differences were detected between respondents and non-respondents. Additionally, a test comparing early and late respondents and types of respondents did not yield significant differences.

To address common-method variance theoretically, the extant research was used to develop a systematic questionnaire and the measures (items) used to build the constructs, which were later statistically refined using exploratory factor analysis. As advised by other researchers (e.g., Tourangeau, Rips and Rasinski, 2000), unfamiliar words, double-barrelled questions, and technical words were avoided. The items were further clustered with different construct items (not in conceptual dimensions). The use of negatively-worded items was avoided because they could distract the respondents' response patterns, creating a source of method bias, as highlighted by Podsakoff, MacKenzie, Lee and Podsakoff (2003). Other steps included informing the respondents about the anonymity of the survey and avoiding single-informant bias—we collected data from different managers (production and operational analysts, IT managers and analysts/big data scientists, and business development analysts). From a statistical perspective, Harman's one-factor test was utilized. The analysis produced multiple factors, explaining the greater variance compared to a single factor solution or other combinations. Although all statistical approaches adopted to control for CMV bias have some advantages and disadvantages (Podsakoff et al., 2003; Malhotra, Kim and Patil, 2006), a reasonable proxy was provided by the marker variable technique (the variable was the number of languages respondents knew) proposed by Lindell and Whitney (2001) with small correlations. The latent factor approach also did not show CMV bias to be an issue (Malhotra et al., 2006).

Although SEM (e.g., maximum likelihood estimate) corrects for the biasing effects of measurement errors (Frone, Russell and Cooper, 1994) or successfully corrects for a small amount of them (DeShon, 1998), researchers still need to control for measurement errors if they use a single indicator approach (DeShon, 1998). In this case, the relevant loadings (i.e., SD * square-root of alpha) and variances for the parcels are fixed (DeShon, 1998; Antonakis, Bendahan and Lalive, 2014). However, as we took a multiple indicator approach, the correction was not required. Omitted biases exist in various forms (for details see Antonakis, Bendahan, Jacquart and Lalive, 2010; Antonakis et al., 2014). One instance of this is represented by researchers testing the validity of a construct while failing to include important variables/constructs. For instance, the measurement of business performance while excluding non-financial performance (e.g., operational and environmental). In this regard, the most important guideline involves considering multiple aspects of theories (Antonakis and Dietz, 2011; Antonakis et al., 2014). Compared to other studies, which often use only one or two dimensions (or few indicators) of business performance, this study includes four, which themselves consist of multiple constructs (e.g., service quality and product quality formed operational construct)—more than 20 indicators with four dimensions were used in relation to business performance. The control variables consisted of respondent types, agrifood networks, number of employees, and annual turnover. The models were checked for any differences based on these groups; we did not find any significant ones when the models were tested based on multi-groups.

Results

The descriptive results are presented in Table 3 with a correlation matrix. The mean values ($\bar{x}$) show that BDS teams' skills and BDD actions, and business performance (BP) were all rated over 4 on a 5-point Likert scale.

[Insert Table 3 here]

A two-stage structural equation modelling approach was used to refine the constructs and to test the hypotheses. First, the measurement models further refined the items and constructs by conducting a series of checks—item reliability, composite reliability, convergent validity, and discriminant validity. One item (BDDA1) was excluded because of low loading (<0.5). Second, the hypotheses were tested by scrutinizing the structural relationships between the constructs. During this process, another item (BDDA4) was excluded because of a high modification index. Two more items from the new business development construct (i.e., partnering with new businesses and focusing on diversification) were deleted. To establish the final model, *p*-value and fit-indices (e.g., CFI $\geq$ 0.90; TLI $\geq$ 0.90; RMSEA $\leq$ 0.08) were also used to check whether the models could be substantially improved or not (Lance, Butts and Michels, 2006; Kline, 2015).

The exploratory results are listed in Table 4. The alpha (α) values, which ranged from 0.79 to 0.93, demonstrated the level of consistency (Lance et al., 2006; Lance, 2011). The loadings (λ; highly significant at $p < 0.01$) provided convergent validity. Additionally, average variance explained (0.61 to 0.70) and construct reliability values (0.87 to 0.94) provided further confidence (Sekaran, 2000). Discriminant validity was measured by means of two methods. First, the correlation between the constructs, see Table 2, did not exceed the value of 0.85 (Kline, 2015), ranging between 0.33 and 0.56. Second, as shown in Table 5, the square of the correlation (ϕ^2) between each pair of constructs was less than the average variance explained (AVE) (Sekaran, 2000; Chiang, Kocabasoglu-Hillmer and Suresh, 2012). Collectively, by investigating the dataset rigorously, the results showed sound psychometric properties.

[Insert Table 4 here]

[Insert Table 5 here]

The development of the second-order construct (i.e., business performance) and its relevant statistics are shown in Figures 3a and 3b. The loadings—which range from 0.71 to 0.83—strongly supported this development and the model fit indices satisfied the recommended cut-off criteria.

Figure 4 and Table 6 (the second to last column) depict the hypotheses and standardized results. Table 6 also lists alternative models and relevant results. Hypothesis H_1 proposes that the use of BDS teams' skills is positively related to business performance. Based on the structural results, the hypothesis is supported with $\beta = 0.28$ at $p < 0.001$. Hypotheses H_2 (the use of BDS teams' skills is positively related to BDD actions) and H_3 (BDD actions are positively related to business performance) are supported with a high degree of significance: $\beta = 0.35$ ($p < 0.001$) and $\beta = 0.55$ ($p < 0.001$).

The last hypothesis stated that BDD actions mediate the relationship between the use of BDS teams' skills and business performance. First, there are (positive) significant relationships between the constructs, as demonstrated in Models 1, 2, and 3 in Table 6. The relationship between the use of BDS teams' skills and business performance is reduced from $\beta = 0.48$*** (5.167) to $\beta = 0.28$*** (3.756), but is still significant, showing a partial mediation. The fit indices, with an R^2 value of 0.49, also strongly support the model; see Column 5 in Table 6.

Additionally, the bootstrapping method shows that the use of BDS teams' skills is positively associated with business performance ($\beta = 0.44$, t = 7.54, $p < 0.001$) and with the mediator (BDD actions) ($\beta = 0.32$, t = 5.33, $p < 0.001$). The mediator is also positively associated with business performance ($\beta = 0.47$, t = 8.69, $p < 0.001$). The direct effect of the use of BDS teams' skills on business performance is reduced ($\beta = 0.29$, t = 5.33, $p < 0.001$), which thus shows partial mediation, with confidence intervals ranging from 0.09 to 0.22 (bias corrected). R^2 and *adjusted*-R^2 are 0.39 and 0.38 respectively.

[Insert Figure 4 here]

[Insert Table 6 here]

To further investigate the relationship between high and low BDD intensive actions and business performance, the surveyed organisations were categorised based upon the high and low intensity of their BDD actions. The results suggest that better business performance results from a higher intensity in the application of BDD actions. Similarly, organisations can improve their performance when BDS teams' skills and BDD actions interact (see Additional Model in Column 5 of Table 6). For strongly big data oriented-organisations, the intensity of BDD actions and BDS teams' skills jointly provide better business performance and, indeed, are key determinants. We conclude that it is worthwhile for big data oriented-organisations to equip their human-resources with better big data skills and relevant knowledge, to enable them to can apply more big data analytics and create better business value by taking BDD actions. These relationships are illustrated by Figure 5.

[Insert Figure 5 here]

Discussion and conclusion

To date, the scholarship on BDS teams' skills, BDD actions, and business performance has been limited (Schoenherr and Speier-Pero, 2015; Akhtar et al., 2018; Wamba et al., 2015). Furthermore, previous scholarship had focussed on the organizational level resources related to big data analytics and had failed to investigate the role played by team level resources (Dutta and Bose, 2015; Akhtar et al., 2018; Davenport and Patil, 2012; Wamba et al., 2015; Sheng et al., 2017), despite recent RBV scholarship in strategic management having demonstrated that knowledge and tangible competencies are possessed by teams within the organization—rather than by the organization itself (Garbuio, King and Lovallo, 2011; Kor and Mesko, 2013; Sheremata, Lee and Medcof, 2010; Felin and Hesterly, 2007; Sheng et al., 2017). Thus, to address this knowledge gap, we simultaneously tested the links between the underlying constructs based on the data collected from our sample of massively connected global business operations. The use of BDS teams' skills and BDD actions have been found to be highly significantly related to business performance. We also found that BDD actions, which play a mediating role, are key determinants for business performance. This means that those organisations that extensively make use of such resources perform better compared to those that focus less on such applications and on the relevant insights drawn from big data.

Theoretical implications

The assertion that big data analytics enhance business performance is now widely accepted. However, scholars have little understanding of how BDS skills are linked to managerial actions and performance. By investigating how BDS teams' skills and BDD actions influence business performance, the results of this research offer important insights into these relationships. The extant research had focussed on exploring the specific technical skills related to big data and the general concepts of big data and had lacked a genuine understanding of how BDD actions are linked with the various dimensions of performance (Schoenherr and Speier-Pero, 2015; Akhtar et al., 2018; Wamba et al., 2015). Little research had thus been conducted with the aim of explicating the linkages between BDS teams' skills, BDD actions and performance. We have brought such concepts together and have emphasised the analytical skills that are imperative for contemporary business operations, which are being inundated with unstructured datasets. Depending on how BDS teams analyse and utilise the insights produced from big data analytics, these very large datasets can provide better insights (Chen and Zhang, 2014; Akhtar et al., 2018). We have further contributed to the multidisciplinary literature on business performance measures by integrating specific and multi-dimensional indicators linked with the data-oriented characteristics of teams and their relevant actions, intersecting with the insights produced form big data analytics. Importantly, we have established links not only between BDS teams' skills and business performance, but also with BDD actions, which play a mediating role (Brown et al., 2011; Akhtar et al., 2018).

Our findings have important implications for RBV scholarship, particularly with regard to the technical-human capital of modern businesses and to the relevant multidisciplinary research. Conventional RBV scholarship—including the RBV of information technology—has overlooked the cross-disciplinary nature of IT management. Recent scholarship conducted from the RBV perspective has begun to explore big data skills and their impacts on organizational performance (Schoenherr and Speier-Pero, 2015; Wamba et al., 2017; Wang and Hajli, 2017); however, these studies have focussed on the functional and technical skills related to big data, rather than on the sets of skills possessed by multi-functional teams and on the actions required to leverage such skills. However, functional big data skills (e.g., the effective use of algorithms or the use of Hadoop) are not rare and difficult-to-imitate resources. In line with the insights drawn from the RBV scholarship—i.e., that managerial teams (e.g. Miller and Shamsie (1996); van der Vegt and Bunderson, 2005) and resource orchestration (e.g. Helfat and Peteraf, 2015; Sirmon et al., 2011) play crucial roles in recognizing and creating value for the organization—our research suggests that it is the skilful bundling of different big data skills in teams and specific managerial actions to leverage big data skills that are rare and difficult to imitate, and can thus lead to competitive advantages. Furthermore, in contrast to the conventional RBV scholarship—which emphasized the exclusive ownership of rare and difficult-to-imitate resources by an organization (e.g., technological patents or IT infrastructures)—big data is often an open or a shared resource, which further underlines the role played by rare and difficult-to-imitate complex bundles of big data skills and collective team-based learning in extracting organizational value from big data sources. In other words, our research points to important differences between the conventional RBV scholarship and the RBV of big data (see Table 7 for a brief summary); we thus think that future scholarship on the RBV of big data needs to re-conceptualize whence the value of big data resources comes.

This view extends the previously theoretical aspects or findings, by which organisations that utilise big data analytics and follow relevant actions significantly improve their productivity by 4-20% (Barton and Court, 2012; Wamba et al., 2015). We demonstrate that big data applications provide multiple business benefits in environmental, operational, social, and financial terms. Big data skills and relative actions also contribute to business development, an aspect that has not yet examined in regard to big data connections (LaValle et al., 2011; Li et al., 2013; Blackburn et al., 2013).

In brief, this study contributes to the extant research on BDS teams' skills, BDD actions, and their impacts on business performance, enhancing our understanding of how data-savvy teams may serve as key drivers of productive actions linked with financial and non-financial outcomes. It is one of the first attempts to connect big data technical skills and the multiple concepts of performance. The interplay of modern skills and data-driven considerations leverages practices that significantly contribute to better business performance.

Practical implications

The application of BDS teams' skills and the taking of suitable BDD actions helps big data oriented-organisations to improve their service and product quality, deliver their products on time, fulfil orders with accuracy, offer more flexibility, improve product defective rates, address product safety issues, and improve product reliability. It also contributes to environment-related factors—such as waste recycling, material and waste-water efficiency, reusable packaging, and energy controls—which are part of an organisation's business performance. The purpose of BDS teams' skills and BDD actions is also to develop businesses both internally and externally. Internally, such data-oriented characteristics keep business units connected and help them to effectively communicate with other interlocking business partners, building enduring relationships, and improving day-to-day processes. Externally, big data and analytics may help to expand business operations within their own field and provide them with opportunities to expand their businesses into other fields in which demand is high. This effectively links them with their business growth strategy of gaining competitive advantages against their competitors. When these non-financial indicators excel, they ultimately contribute to cash-flows, profitability, and return on investment. Thus, managers should consider and apply the relevant aspects of big data analytics to improve the many dimensions of their business performance by effectively using their BDS teams and taking BDD actions aimed at developing a competitive advantage.

Big data is generated from both within the corporate boundaries and the outside world, which entails the need for effective collaboration both between and within organizations. It ultimately provides two-fold applications for those organisations that look for internal and external opportunities to improve their overall business performance. Multi-skilled BDS teams may explore internal data and detect patterns in their end-to-end business operations, increasing their supply chain and operational visibility. Any unusual patterns that go against predictive outcomes can then be tackled through BDD actions, backed up by insights obtained from big data exploration and visualisation. This can particularly contribute to operational performance. Visibility is especially important for single source-dependent supply chains, as these are more prone to risk because they mainly depend on their central distribution centre. A recent example (i.e., one that occurred in 2018) of this was provided by KFC, when many of its UK stores were forced to close due to a single source failure. Big data can help to avoid this type of incident by improving the visibility of and predicting operations more accurately—in fact, in real time with the use of real time analytics. Second, big data produced from external sources assist in developing new businesses. Multi-skilled BDS teams can be utilised to explore external business opportunities (e.g., opening new branches where more demand is predicted) and customer feedback, which is often expressed on different websites and social media. This especially comes through unstructured data and helps organisations to improve their product and service quality.

There are also practical implications for universities. As a result of the emerging integration of informatics and data science in business schools, many universities are now offering MSc programmes in big data analytics or business intelligence—as an interdisciplinary degree between business schools, computer science, statistics, and mathematics. However, the integration, in these courses, of technical content (e.g., IT programming and coding skills, business mathematics and statistics, machine learning, and optimisation techniques) is still questionable. Our research infers that business data scientists need more technical skills. Thus, an interdisciplinary curriculum development approach adopted between various departments (business, computing, mathematics, and statistics) would be useful. Another option could be the retraining of business school staff members, who could upgrade their skills and transfer them to students. If business schools do not undertake these developments, non-business schools might take over to meet the industrial demand. Additionally, business experts/teachers, who already have business degrees but do not have technical skills, may consider completing pure technical courses (e.g., Data Mining and Applications Graduate Certificate, Stanford University), which could help them to be better data science teachers. The relevant free online short courses (e.g., Coursera and edX) could further help non-technical teachers to build foundations for advanced courses in big data analytics and business intelligence. Most crucially, our research points to the importance of teaching not merely distinct functional skills related to big data, but also of training to work in multi-skilled teams that can combine different sets of skills and ultimately leverage them to create value for the organization.

Limitations and future research

Our study is affected by the limitations of survey research in general. The theoretical framework was tested using data from specific industries, and the underlying constructs may behave differently in other ones. Therefore, future research could use data from other industries and settings. Also, big data technology and analytical techniques are subject to rapid change and the timing of our research may have affected its findings. Thus, future studies may avail themselves of more advanced big data technologies with different impacts on business performance.

Future research would need to focus on unstructured data, how they can help to make automated-decisions and develop evidence-based opportunities for policymaking. Roughly, 90% of big data has been generated in the last few years and their production is increasing exponentially. This trend has generated many challenges, particularly in relation to big data quality and cybersecurity issues. Thus, there are many opportunities for future research in these domains. Nonetheless, our study has yielded interesting insights into the intersection of BDS teams' skills, BDD actions, and business performance; we hope that these can help future researchers to better navigate this complex topic.

References

Akhtar, P., Z. Khan, J. G. Frynas, Y. K. Tse and R. Rao-Nicholson (2018). 'Essential Micro-foundations for Contemporary Business Operations: Top Management Tangible Competencies, Relationship-based Business Networks and Environmental Sustainability', *British Journal of Management*, **29**, pp. 43-63.

Anderson, J. L., L. D. Jolly and A. E. Fairhurst (2007). 'Customer relationship management in retailing: A content analysis of retail trade journals', *Journal of Retailing and Consumer Services*, **14**, pp. 394-399.

Antonakis, J., S. Bendahan, P. Jacquart and R. Lalive (2010). 'On making causal claims: A review and recommendations', *The Leadership Quarterly*, **21**, pp. 1086-1120.

Antonakis, J., S. Bendahan and R. Lalive (2014). 'Causality and endogeneity: Problems and solutions'. *The Oxford handbook of leadership and organizations.* Oxford: Oxford University Press.

Antonakis, J. and J. Dietz (2011). 'More on testing for validity instead of looking for it', *Personality and Individual Differences*, **50**, pp. 418-421.

APICS (2012). 'Big Data Insights and Innovations Executive Summary, available http://www.apics.org/docs/default-source/industry-content/big-data-report.pdf?Status=Master'.

Aral, S. and P. Weill (2007). 'IT assets, organizational capabilities, and firm performance: How resource allocations and organizational differences explain performance variation', *Organization Science*, **18**, pp. 763-780.

Aramyan, L. H., A. G. O. Lansink, J. G. Van Der Vorst and O. Van Kooten (2007). 'Performance measurement in agri-food supply chains: a case study', *Supply Chain Management: An International Journal*, **12**, pp. 304-315.

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

Barney, J. B. and A. M. Arikan (2001). 'The resource-based view: Origins and implications', *Handbook of strategic management*, **10.1111/b.9780631218616.2006.00009.x**.

Barton, D. and D. Court (2012). 'Making advanced analytics work for you', *Harvard business review*, **90**, pp. 78-83.

Bizer, C., P. Boncz, M. L. Brodie and O. Erling (2012). 'The meaningful use of big data: four perspectives--four challenges', *Acm Sigmod Record*, **40**, pp. 56-60.

Blackburn, R. A., M. Hart and T. Wainwright (2013). 'Small business performance: business, strategy and owner-manager characteristics', *Journal of Small Business and Enterprise Development*, **20**, pp. 8-27.

Brown, B., M. Chui and J. Manyika (2011). 'Are you ready for the era of ‘big data’', *McKinsey Quarterly*, **4**, pp. 24-35.

Brynjolfsson, E., L. M. Hitt and H. H. Kim (2011). 'Strength in numbers: How does data-driven decisionmaking affect firm performance?', *Available at SSRN: http://ssrn.com/abstract=1819486 or http://dx.doi.org/10.2139/ssrn.1819486*.

Chen and Y. Zhang (2014). 'Data-intensive applications, challenges, techniques and technologies: A survey on Big Data', *Information Sciences*, **275**, pp. 314-347.

Chen, H., R. H. Chiang and V. C. Storey (2012). 'Business Intelligence and Analytics: From Big Data to Big Impact', *MIS Quarterly*, **36**, pp. 1165-1188.

Chiang, C.-Y., C. Kocabasoglu-Hillmer and N. Suresh (2012). 'An empirical investigation of the impact of strategic sourcing and flexibility on firm's supply chain agility', *International Journal of Operations & Production Management*, **32**, pp. 49-78.

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

Collings, D. G., K. Mellahi and W. F. Cascio (2017). *The Oxford Handbook of Talent Management*, Oxford University Press.
Crook, T. R., D. J. Ketchen, J. G. Combs and S. Y. Todd (2008). 'Strategic resources and performance: a meta-analysis', *Strategic Management Journal,* **29**, pp. 1141-1154.
Davenport, T. H. (2006). 'Competing on analytics', *Harvard business review,* **84**, pp. 1-10.
Davenport, T. H. and D. Patil (2012). 'Data scientist', *Harvard business review,* **90**, pp. 70-76.
DeShon, R. P. (1998). 'A cautionary note on measurement error corrections in structural equation models', *Psychological methods,* **3**, pp. 412-423.
Dutta, D. and I. Bose (2015). 'Managing a big data project: the case of ramco cements limited', *International Journal of Production Economics,* **165**, pp. 293-306.
Erevelles, S., N. Fukawa and L. Swayne (2016). 'Big Data consumer analytics and the transformation of marketing', *Journal of Business Research,* **69**, pp. 897-904.
Fainshmidt, S., A. Smith and O. Guldiken (2017). 'Orchestrating the flow of human resources: Insights from Spanish soccer clubs', *Strategic organization,* **1476127017689969**.
Fawcett, S. E., C. Wallin, C. Allred, A. M. Fawcett and G. M. Magnan (2011). 'Information technology as an enabler of supply chain collaboration: a dynamic-capabilities perspective', *Journal of supply chain management,* **47**, pp. 38-59.
Felin, T. and W. S. Hesterly (2007). 'The knowledge-based view, nested heterogeneity, and new value creation: Philosophical considerations on the locus of knowledge', *Academy of Management Review,* **32**, pp. 195-218.
Fortunato, S. (2010). 'Community detection in graphs', *Physics Reports,* **486**, pp. 75-174.
Frone, M. R., M. Russell and M. L. Cooper (1994). 'Relationship between job and family satisfaction: Causal or noncausal covariation?', *Journal of Management,* **20**, pp. 565-579.
Garbuio, M., A. W. King and D. Lovallo (2011). 'Looking Inside Psychological Influences on Structuring a Firm’s Portfolio of Resources', *Journal of Management,* **37**, pp. 1444-1463.
Gibson, C. B., M. J. Waller, M. A. Carpenter and J. M. Conte (2007). 'Antecedents, consequences, and moderators of time perspective heterogeneity for knowledge management in MNO teams', *Journal of Organizational Behavior,* **28**, pp. 1005-1034.
Helfat, C. E. and M. A. Peteraf (2015). 'Managerial cognitive capabilities and the microfoundations of dynamic capabilities', *Strategic Management Journal,* **36**, pp. 831-850.
Hitt, M. A., R. D. Ireland, D. G. Sirmon and C. A. Trahms (2011). 'Strategic entrepreneurship: creating value for individuals, organizations, and society', *The Academy of Management Perspectives,* **25**, pp. 57-75.
Katal, A., M. Wazid and R. Goudar (2013). 'Big data: Issues, challenges, tools and Good practices'. *Contemporary Computing (IC3), 2013 Sixth International Conference on.* pp. 404-409. IEEE.
Kline, R. B. (2015). *Principles and practice of structural equation modeling,* The Guilford Press, New York, NY.
Kor, Y. Y. and A. Mesko (2013). 'Dynamic managerial capabilities: Configuration and orchestration of top executives' capabilities and the firm's dominant logic', *Strategic Management Journal,* **34**, pp. 233-244.
Kraaijenbrink, J., J.-C. Spender and A. J. Groen (2010). 'The resource-based view: A review and assessment of its critiques', *Journal of Management,* **36**, pp. 349-372.
Kyrgidou, L. P. and S. Spyropoulou (2013). 'Drivers and performance outcomes of innovativeness: an empirical study', *British Journal of Management,* **24**, pp. 281-298.

Lance, C. E. (2011). 'More statistical and methodological myths and urban legends', *Organizational Research Methods,* **14**, pp. 279-286.
Lance, C. E., M. M. Butts and L. C. Michels (2006). 'The sources of four commonly reported cutoff criteria what did they really say?', *Organizational Research Methods,* **9**, pp. 202-220.
Lantz, B. (2015). *Machine learning with R,* Packt Publishing Ltd.
LaValle, S., E. Lesser, R. Shockley, M. S. Hopkins and N. Kruschwitz (2011). 'Big data, analytics and the path from insights to value', *MIT Sloan Management Review,* **52**, p. 21.
Li, Y., X. Wang, L. Huang and X. Bai (2013). 'How does entrepreneurs' social capital hinder new business development? A relational embeddedness perspective', *Journal of Business Research,* **66**, pp. 2418-2424.
Liben-Nowell, D. and J. Kleinberg (2007). 'The link-prediction problem for social networks', *Journal of the American society for information science and technology,* **58**, pp. 1019-1031.
Lindell, M. K. and D. J. Whitney (2001). 'Accounting for common method variance in cross-sectional research designs', *Journal of applied psychology,* **86**, pp. 114-121.
Malhotra, N. K., S. S. Kim and A. Patil (2006). 'Common method variance in IS research: A comparison of alternative approaches and a reanalysis of past research', *Management Science,* **52**, pp. 1865-1883.
Miao, C., J. E. Coombs, S. Qian and D. G. Sirmon (2017). 'The mediating role of entrepreneurial orientation: A meta-analysis of resource orchestration and cultural contingencies', *Journal of Business Research,* **77**, pp. 68-80.
Miller, D. and J. Shamsie (1996). 'The resource-based view of the firm in two environments: The Hollywood film studios from 1936 to 1965', *Academy of Management Journal,* **39**, pp. 519-543.
Nath, P., S. Nachiappan and R. Ramanathan (2010). 'The impact of marketing capability, operations capability and diversification strategy on performance: A resource-based view', *Industrial Marketing Management,* **39**, pp. 317-329.
Ndofor, H. A., D. G. Sirmon and X. He (2011). 'Firm resources, competitive actions and performance: investigating a mediated model with evidence from the in-vitro diagnostics industry', *Strategic Management Journal,* **32**, pp. 640-657.
Nevo, S. and M. R. Wade (2010). 'The formation and value of IT-enabled resources: antecedents and consequences of synergistic relationships', *MIS Quarterly,* pp. 163-183.
Pearce, C. L. and M. D. Ensley (2004). 'A reciprocal and longitudinal investigation of the innovation process: The central role of shared vision in product and process innovation teams (PPITs)', *Journal of Organizational Behavior,* **25**, pp. 259-278.
Peteraf, M. A. (1993). 'The cornerstones of competitive advantage: A resource-based view', *Strategic Management Journal,* **14**, pp. 179-191.
Podsakoff, P. M., S. B. MacKenzie, J.-Y. Lee and N. P. Podsakoff (2003). 'Common method biases in behavioral research: a critical review of the literature and recommended remedies', *Journal of applied psychology,* **88**, pp. 879-903.
Provost, F. and T. Fawcett (2013). 'Data science and its relationship to big data and data-driven decision making', *Big Data,* **1**, pp. 51-59.
Rao, P., O. la O'Castillo, P. S. Intal Jr and A. Sajid (2006). 'Environmental indicators for small and medium enterprises in the Philippines: An empirical research', *Journal of Cleaner Production,* **14**, pp. 505-515.
Real, J. C., J. L. Roldán and A. Leal (2014). 'From entrepreneurial orientation and learning orientation to business performance: analysing the mediating role of organizational

learning and the moderating effects of organizational size', *British Journal of Management*, **25**, pp. 186-208.

Roche, C. (2017). 'AnalytiXagility: Creating a Platform to Power the Next Generation of Clinical and Translational Informatics, accessed 05/11/2017', *Aridhia*, *https://d1fto35gcfffzn.cloudfront.net/big-data/case-study/CaseStudy_Aridhia.pdf*, pp. 1-4.

Schoenherr, T. and C. Speier-Pero (2015). 'Data Science, Predictive Analytics, and Big Data in Supply Chain Management: Current State and Future Potential', *Journal of Business Logistics*, **36**, pp. 120-132.

Sekaran, U. (2000). *Research methods for business: A skill-building approach*, John Wiley & Sons.

Shah, R. and P. T. Ward (2007). 'Defining and developing measures of lean production', *Journal of Operations Management*, **25**, pp. 785-805.

Sheng, J., J. Amankwah-Amoah and X. Wang (2017). 'A multidisciplinary perspective of big data in management research', *International Journal of Production Economics*.

Sheremata, W., P. H. Lee and T. Medcof (2010). '"Any" industry experience, diversity, and systems innovation: The complexities of TMT composition'. *Academy of Management Annual Meeting Proceedings, DOI: 10.5465/AMBPP.2010.54503678.*

Sirmon, D. G. and M. A. Hitt (2009). 'Contingencies within dynamic managerial capabilities: Interdependent effects of resource investment and deployment on firm performance', *Strategic Management Journal*, **30**, pp. 1375-1394.

Sirmon, D. G., M. A. Hitt, J. L. Arregle and J. T. Campbell (2010). 'The dynamic interplay of capability strengths and weaknesses: investigating the bases of temporary competitive advantage', *Strategic Management Journal*, **31**, pp. 1386-1409.

Sirmon, D. G., M. A. Hitt, R. D. Ireland and B. A. Gilbert (2011). 'Resource orchestration to create competitive advantage: Breadth, depth, and life cycle effects', *Journal of Management*, **37**, pp. 1390-1412.

Stewart, G. L. and M. R. Barrick (2000). 'Team structure and performance: Assessing the mediating role of intrateam process and the moderating role of task type', *Academy of Management Journal*, **43**, pp. 135-148.

Tambe, P. (2014). 'Big data investment, skills, and firm value', *Management Science*, **60**, pp. 1452-1469.

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

Tourangeau, R., L. J. Rips and K. Rasinski (2000). *The psychology of survey response*, Cambridge University Press.

UK-Immigration (2017). 'Immigration Rules Appendix K: Shortage Occupation List', *https://www.gov.uk/guidance/immigration-rules/immigration-rules-appendix-k-shortage-occupation-list*, **accessed on 05/11/2017**.

Van Der Vegt, G. S. and J. S. Bunderson (2005). 'Learning and performance in multidisciplinary teams: The importance of collective team identification', *Academy of Management Journal*, **48**, pp. 532-547.

Wamba, S. F., S. Akter, A. Edwards, G. Chopin and D. Gnanzou (2015). 'How ‘big data’can make big impact: Findings from a systematic review and a longitudinal case study', *International Journal of Production Economics*, **165**, pp. 234-246.

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

Wang, Y. and N. Hajli (2017). 'Exploring the path to big data analytics success in healthcare', *Journal of Business Research,* **70**, pp. 287-299.

Wu, X., V. Kumar, J. R. Quinlan, J. Ghosh, Q. Yang, H. Motoda, G. J. McLachlan, A. Ng, B. Liu and S. Y. Philip (2008). 'Top 10 algorithms in data mining', *Knowledge and Information Systems*, **14**, pp. 1-37.

Zhang, M., Y. K. Tse, B. Doherty, S. Li and P. Akhtar (2016). 'Sustainable supply chain management: Confirmation of a higher-order model', *Resources, Conservation and Recycling,* **128**, pp. 206-221.

Table 1. Key relevant studies on big data analytics

Key studies	Focus	Study types/methods
(Cohen et al., 2009)	Magnetic, agile and deep big data analysis with effective database systems	A case study of advertising networks at Fox Audience Network
(LaValle et al., 2011)	Big data (BD), analytic, insights and value creation BD applications, challenges, techniques, and technologies	Interviews and a survey of 3000 business executives data from executives, managers and analysts
(Tambe, 2014)	BD investment, skills, and firm value	Regression analysis, using data from LinkedIn
(Dutta and Bose, 2015)	BD management and implementation	A case study of big data project at a manufacturing company in India
(Schoenherr and Speier-Pero, 2015)	The academic integration of data science, predictive analytics, and BD in supply chain programmes	A large scale survey of supply chain professionals to explore current and future aspects of BD
(Wamba et al., 2015)	BD and its impact on business operations	A case study and systematic review to explore the operational and strategic impacts of BD
(Tan et al., 2015)	BD enhancing supply chain innovation capabilities	A deduction graph technique and case studies for analytic infrastructure
(Erevelles et al., 2016)	BD, insights, marketing activities (product, price, place and promotion), sustainable competitive advantage	A conceptual paper – proposed a theoretical framework
(Wamba et al., 2017)	A BD analytics capability and performance	An online survey of Chinese IT managers and business analysts
(Wang and Hajli, 2017)	BD analytics capabilities and benefits	Case studies of healthcare providers
(Sheng et al., 2017)	Key BD themes emerging in management studies	A systematic literature review of BD research in management since 2005
(Akhtar et al., 2018)	Top management tangible competencies (i.e., big data skills), relationship-building, and sustainability	A survey of top management representatives in food import and export firms headquartered in the UK and New Zealand

Table 2. Sample characteristics

	Category	No	%
Job titles	Production and operational analysts	90	38
	IT managers and analysts/big data scientists	95	40
	Business development analysts	55	22
Agrifood networks	Veg. & fruits growers	103	43
	Meat suppliers	86	36
	Dairy producers	51	21
Employees	<20	66	28
	20-100	97	40
	101-200	77	32
Turnover($m)	<15	46	19
	15-60	194	81
Total		240	100

Table 3. Descriptive statistics.

Constructs	$\overline{x}$	σ	1	2	3
1. Big data-savvy (BDS) teams' skills	4.22	0.31			
2. Big data-driven (BDD) actions	4.29	0.39	0.33		
3. Business performance (BP)	4.15	0.32	0.44	0.56	

$\overline{x}$ (mean); σ (standard deviation); n=240; all correlations are significant at $p < 0.01$

Table 4. Exploratory factor analysis and quality checks

Constructs	Indicators	α	λ	AVE	C.R
Big data-savvy teams' (DDSBMs) skills	BDSTS1	0.87	0.64	0.63	0.89
	BDSTS2		0.66		
	BDSTS3		0.69		
	BDSTS4		0.68		
	BDSTS5		0.75		
	BDSTS6		0.79		
	BDSTS7		0.84		
	BDSTS8		0.75		
Big data-driven actions (BDDAs)	BDDA2	0.93	0.85	0.70	0.94
	BDDA3		0.82		
	BDDA5		0.82		
	BDDA6		0.89		
	BDDA7		0.88		
	BDDA8		0.81		
	BDDA9		0.76		
Business performance: Four dimensions of performance	BPEP	0.79	0.78	0.61	0.87
	BPOP		0.82		
	BPNBD		0.77		
	BPFP		0.77		

Indicators BDDA1 and BDDA4 were deleted because of low loading/high modification index; α = items reliability; λ = loadings; AVA =average variance explained; C.R =construct reliability;

Table 5. Second method for discriminant validity

	Statistics			Condition met
Constructs	ϕ	ϕ^2	AVE	$\phi^2 <$ AVE
DDSTS & BDDA	0.33	0.11^a	0.67^b	Yes
DDSTS & BP	0.44	0.19	0.62	Yes
BDDA & BP	0.56	0.31	0.66	Yes

ϕ=correlation between factors, ${}^a\phi^2$, 0.33*0.33 = 0.11; ^{b}AVE, (0.63+0.70)/2 = 0.67 (AVE DDSBMs & BDDAs)

Table 6. Models, structural results and fit indices

Variables and statistics	Model 1	Model 2	Model 3	Final model	Additional Model
DSTS → BP	0.48*** (5.167)			0.28*** (3.756)	0.23*** (2.960)
DDSTS → BDDA		0.35*** (4.537)		0.35*** (4.566)	0.36*** (4.683)
BDDA → BP			0.65*** (8.049)	0.55*** (7.055)	0.53*** (6.872)
DDSTS * BDDA → BP					0.14** (2.157)
R^2	0.23	0.12	0.42	0.49	0.50
χ^2/df	2.376	1.552	1.337	1.522	1.472
RMSEA	0.076	0.048	0.38	0.047	0.044
CFI	0.938	0.975	0.990	0.967	0.968
TLI	0.960	0.970	0.988	0.962	0.963
IFI	0.939	0.975	0.99	0.968	0.968

Significant at $p < 0.01$(***) and $p < 0.05$ (**)

Table 7. Key differences between conventional RBV and RBV of big data

	Conventional RBV	**RBV of big data**
Definition of a resource	All assets, capabilities, organizational processes, firm attributes, information, knowledge, etc. controlled by a firm	All assets and capabilities that can provide a basis for big data collection, storage and analytics
Control of the resource	Full ownership of resources by the organization	Shared ownership of big data resources
Nature of a capability	Predominantly functional (e.g., technical or marketing capabilities)	Multi-disciplinary; combining skills from mathematics, operations research, statistics, machine learning and business applications
Basis of competitive advantage	The ability to create, appropriate, and sustain value from internally owned valuable, rare, difficult to imitate and non-substitutable resources and capabilities	The ability to create and sustain value and insights from the complex bundles of big data skills and collective team-based learning

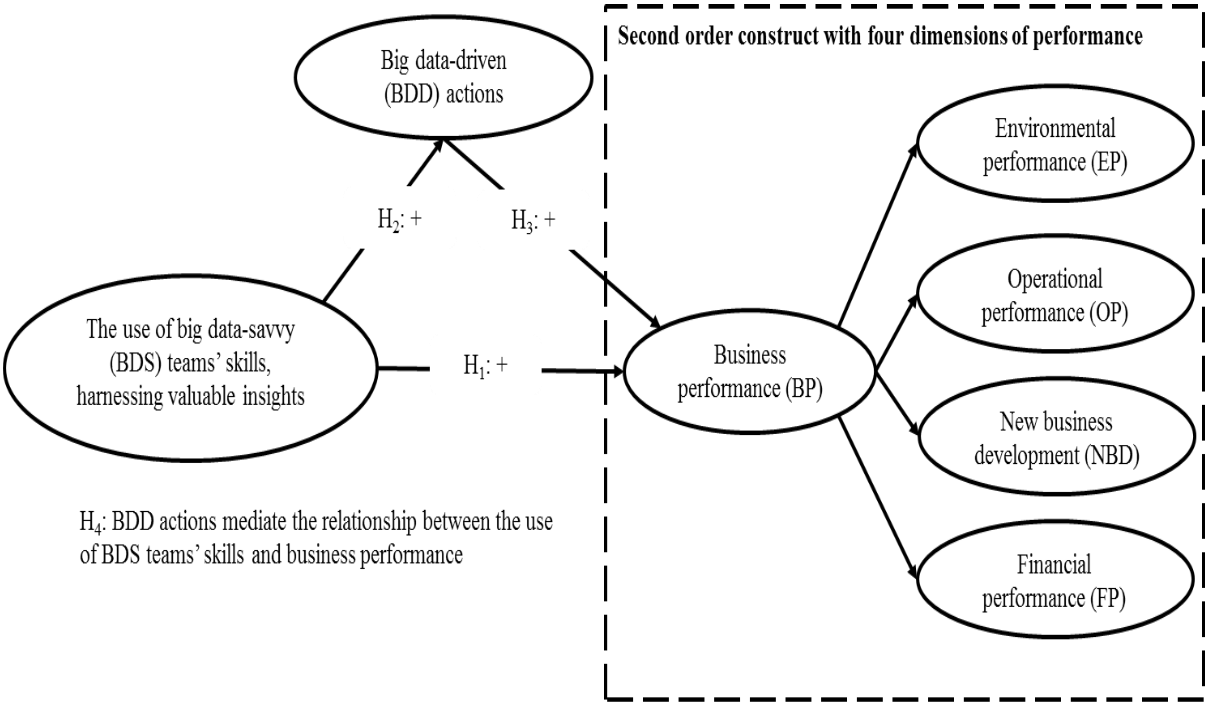


Figure 1. Framework of BDS teams' skills, BDD actions and business performance

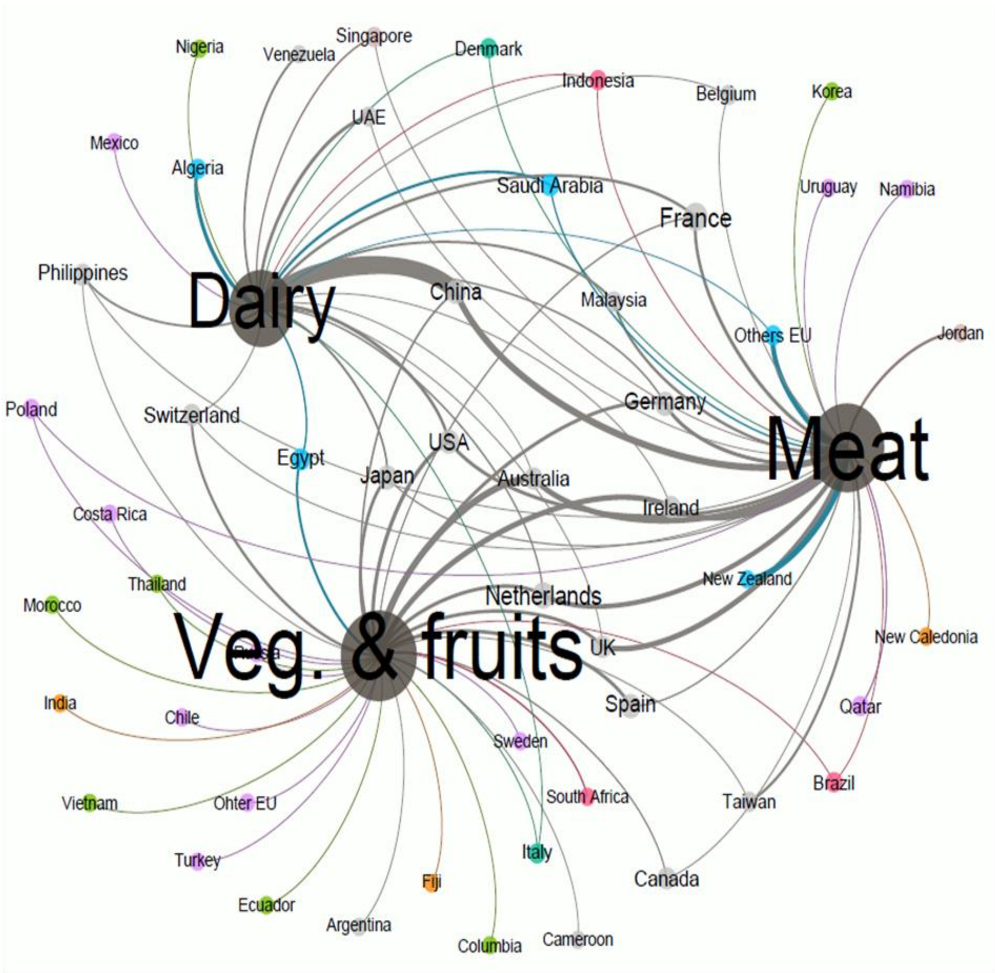


Figure 2. Selected agrifood supply chain networks

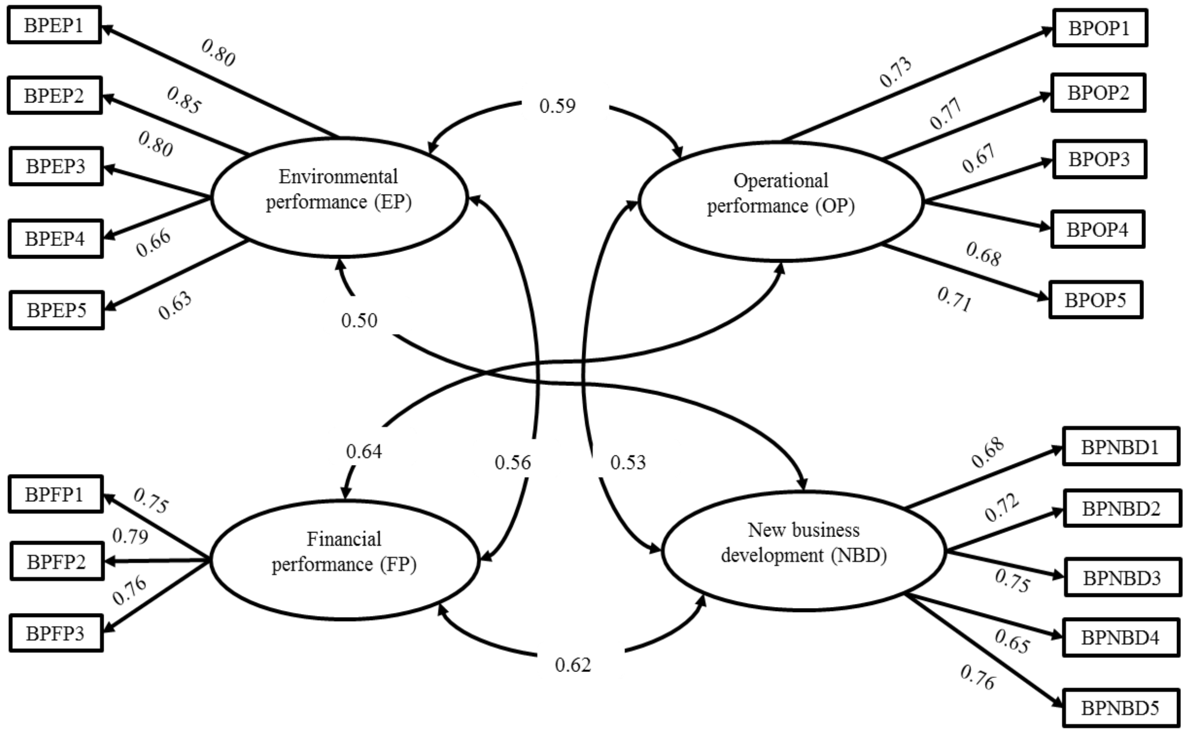
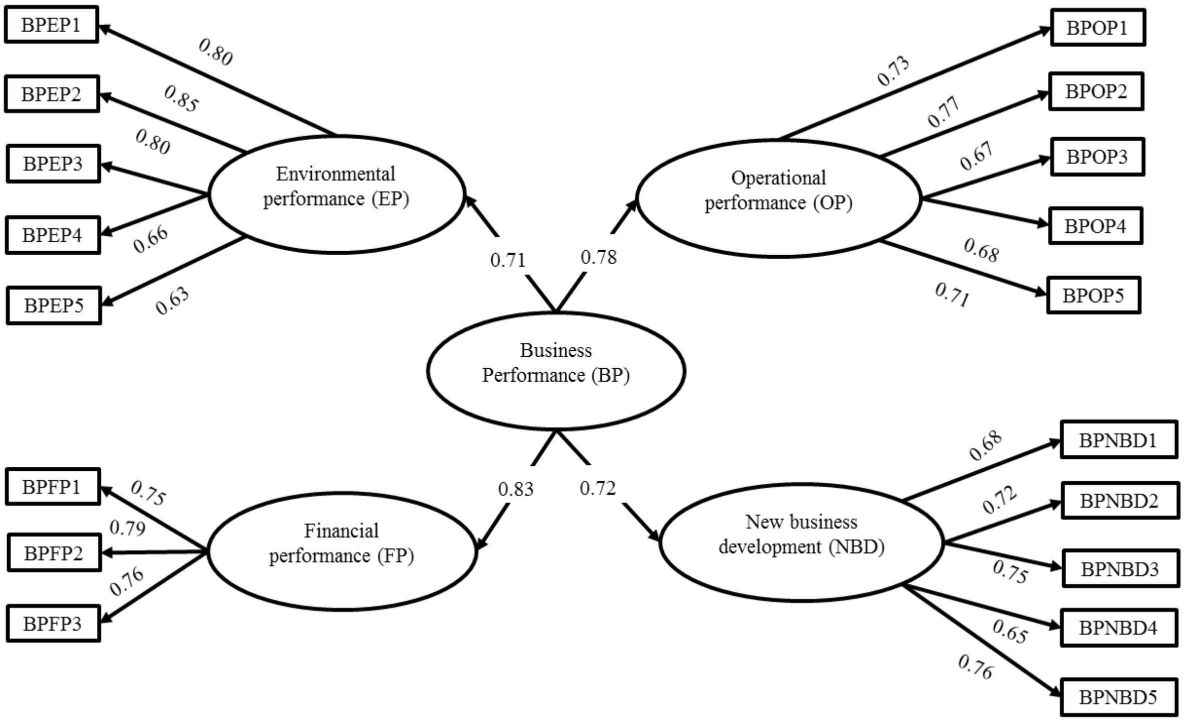


Figure 3a Business performance as a second-order construct



All loadings and correlations were significant at $p < 0.01$; $\chi^2/df = 1.803$; CFI = 0.942; TLI = 0.933; IFI = 0.943; RMSEA = 0.058

Figure 3b Business performance as a second-order construct

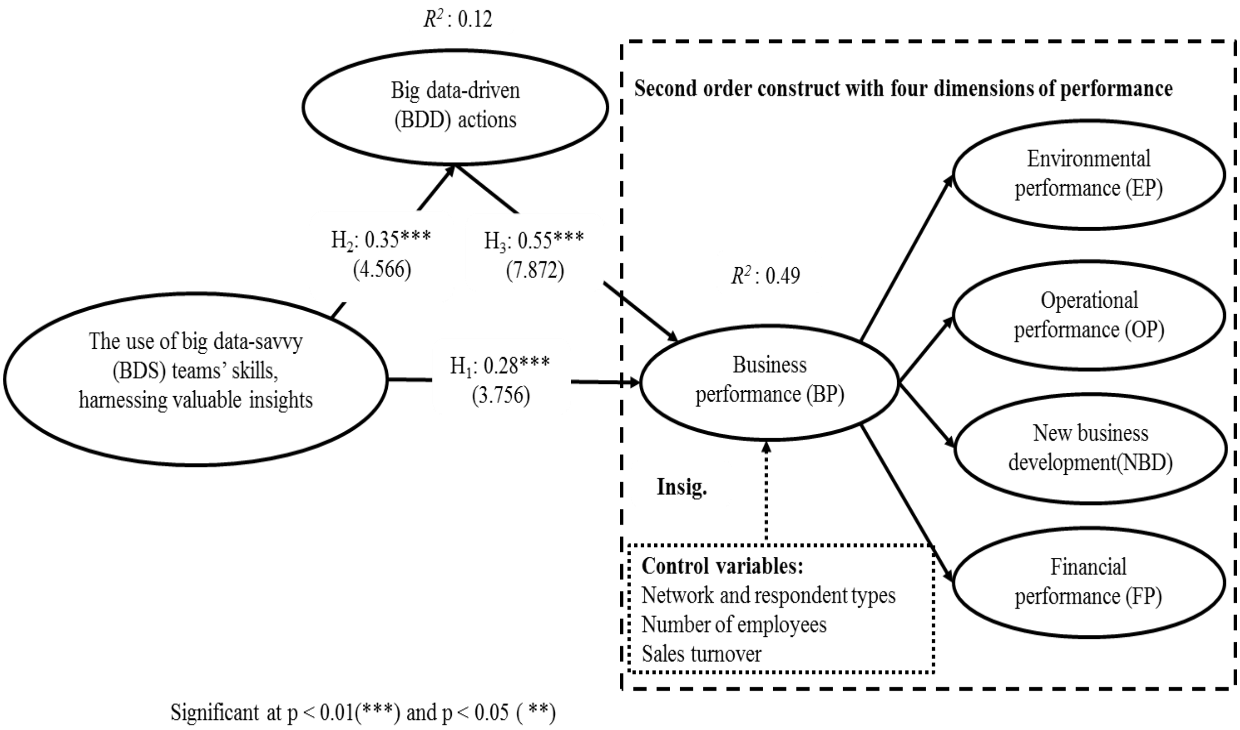


Figure 4. Framework of BDS teams' skills, BDD actions and business performance

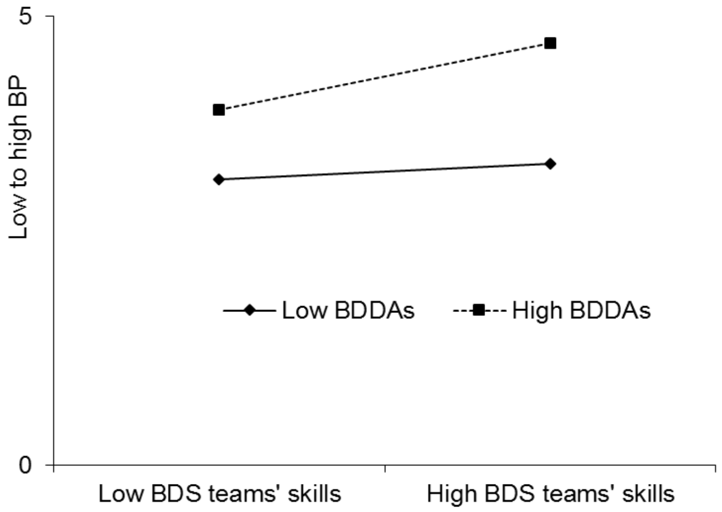


Figure 5. Interaction effects