Summer 6-27-2016

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Abstract

Big Data Analytics has been a 'hot topic' for industry and academic during the past few years. This paper examines what constitutes Big Data Analytics (BDA) and how it relates to organizational performance. It also investigates what other factors influence this relationship, whether BDA leads to more data-driven decision-making (DDDM) and whether the latter is really superior to less informed decision-making. The study first operationalizes Big Data Analytics, and then develops a research model which manifests the direct and indirect relationships between analytic capability, DDDM, and organizational performance.

Keywords: Big Data, Big Data Analytics, Organizational Performance, Data-Driven Decision-making, Economics of IT

1 INTRODUCTION

During the past few years, the words 'Big Data' and 'Big Data Analytics' have become increasingly important for both academics and business professionals in information technology (IT)-related fields and other disciplines. Furthermore, executives increasingly acknowledge the potential benefits associated with Big Data (Accenture 2013; NewVantage Partners 2014; Schroeck et al. 2012) and global private and public investment in Big Data has reached billions of dollars per annum (Gartner Research 2015; Palaskas 2015; Rossino 2015). During the past five years, the Australian Government invested $250 million to transform the Australian Bureau of Statistics infrastructure to effectively and efficiently exploit Big Data sources[1]. Big Data has become a popular term which essentially represents the fact that data generated and available today is 'big' in terms of volume, variety, and velocity (CGMA 2013; Chen et al. 2012; Davenport 2014; McAfee & Brynjolfsson 2012).

But being 'big' does not per se make data useful. It is rather the *insights* gained from analyzing the data which provide benefits (Gartner Research 2011; King 2013), which in turn requires organizations to develop or acquire analytic capabilities (Davenport 2014). Equipped with Big Data Analytics experts (Davenport & Patil 2012), who can provide such insights from data (NewVantage Partners 2016), organizations are deemed to achieve competitive advantages (Barton & Court 2012; CGMA 2013; Chen et al. 2012; Davenport 2014).

It has been claimed that Big Data Analytics (BDA) can lead to better decision-making and improve organizational performance (Bange & Janoschek 2014), because it provides managers with insights to better understand their businesses, customers, and environments, as well as to base their decisions on facts rather than intuition (Barské-Erdogan 2014; Davenport 2014). High-performing organizations believe that BDA is a critical differentiator and a key to growth (Deloitte 2014; IBM Software 2013; LaValle et al. 2011; Schroeck et al. 2012). It has even been claimed that Big Data is a paradigm shift that changes the way organizations deal with data and the way they run their businesses (Vasarhelyi et al. 2015). However, none of these claims have so far been confirmed by rigorous empirical research results.

The anecdotal 'evidence' of the benefits associated with BDA also often ignores that they come at a cost. Executives still struggle to understand and implement BDA strategies effectively (CGMA 2013). Considering the many well-documented cases of unsuccessful deployment of enterprise resource planning (ERP) and business intelligence (BI) systems (Grabski et al. 2011), one has to question how many organizations can really make sense of Big Data. In addition, it is unclear to what extent managers actually use the available output of BDA to support their decisions. Early research has shown that personal attributes can affect the degree of acceptance of new technology, but very little is known precisely what factors encourage *data-driven* decision-making (DDDM) in the Big Data context.

BDA is often praised as a promising source of benefits or even a competitive advantage, but apart from anecdotal evidence (case studies), very little is known about such effects, which prompts the following main research question: *Does BDA have a positive impact on organizational performance?*

The quest for an answer to this question first of all requires a clarification of what constitutes 'Big Data Analytics' and how it can actually be operationalized (and measured). Apart from data, the core 'ingredients' for BDA are *analytic resources*, i.e. *analytic skills* and *analytic tools* (Davenport 2014; Stubbs 2014). Numerous analytic methods have been developed and applied, and there are many analytic software tools available on the market (or even for free). However, does the (increased) use of those methods and tools lead to superior performance? How many analytic skills are required to

[1] http://www.abs.gov.au/websitedbs/Corporate.nsf/Home/government+investment+in+the+ABS

achieve such benefits? Furthermore, it is worthwhile investigating whether DDDM influences the relationship between BDA and performance. Davenport (2014) claims that (higher levels) of BDA can have a positive impact on (the quality of) managerial decision-making. In addition, research shows that in high-performing organizations, important decisions are made rationally and involve less intuition than in low-performing organizations (Guillemette et al. 2014). Therefore, the second research question is *To what extent do managers use analytic output in the decision-making process, and does such use actually lead to better performance?*

The motivation that drives this study is threefold. First, many claims have been made that BDA will improve business performance (Bange & Janoschek 2014), but so far no larger-scale rigorous research has been conducted to analyze how BDA can improve organizational performance. Second, our understanding and measurement of Big Data and BDA are sparse. Organizations realize the existence and importance of Big Data (Accenture 2013; NewVantage Partners 2014; Schroeck et al. 2012); nonetheless, no empirical studies have attempted to operationalize Big Data and BDA. Third, very little is known about mechanisms contributing to the achievement of benefits from BDA, in particular whether managers actually use analytics output for decision-making.

This study is expected to contribute to previous literature and professional practice in four important ways. First, this study will provide a better understanding of the effects of BDA on organizational performance. Second, this study is also one of the earliest research projects which synthesizes major elements mentioned in prior literature, including expertise, functionality, Big Data characteristics, and managerial decision-making. Third, this study offers a significant opportunity to obtain a better understanding of what level of BDA is required to improve decision-making and organizational performance. Fourth, the research results can be used by industry as a guideline how to deal with Big Data and utilize their BDA effectively. Educational institutions can design their data analytics courses/degrees accordingly, and software vendors can benchmark the analytic tools of their software functions and features.

2 BACKGROUND/LITERATURE REVIEW

2.1 Big Data

Big Data refers to a set of techniques and technologies that requires new forms of integration in order to uncover hidden value from large datasets that are diverse, complex, and of a massive scale. Big Data is characterized by its three Vs: volume, variety, and velocity (CGMA 2013; Chen et al. 2012; Davenport 2014; McAfee & Brynjolfsson 2012). The volume of Big Data is massive, so conventional hardware and software are incapable of handling it within a proper time-frame (Moffitt & Vasarhelyi 2013). Data in organizations has become more complex, because it includes not only traditional relational data, but also raw, semi-structured, and unstructured data from various sources. Data scope is expanding, and research shows that data from various sources would enrich an organization's analytics (Moffitt & Vasarhelyi 2013). Velocity refers to both the speed of data generation and of data processing. Data today is generated, changed, and removed more frequently (Zikopoulos et al. 2011) and consequently, organizations need new platforms and tools for analyzing it.

2.2 Big Data Analytics

Cao et al. (2015) define BDA as the procedure to discover and manage useful information, patterns, or conclusions from Big Data to support managerial decisions. BDA has an important impact on decision-making processes by applying scientific methods to solve problems that were previously impossible to solve, because either the data or the analytic tools did not exist (Davenport 2014; Parmar et al. 2014). BDA no longer involves just traditional hypothesis-based statistical analysis, but also machine learning, predictive modeling, faster processing tools, high-performance analytics environments, and visual analytics (Chen et al. 2012; Dhar 2013; Dyché 2014). BDA is a potential benefit-generator for any organization in the Big Data information age (McAfee & Brynjolfsson 2012). But successful implementation of BDA requires people with skills to handle Big Data, extract meanings, and develop insights (Davenport & Patil 2012; Stubbs 2014). Successful implementation of BDA, analytic skills, appropriated hardware and software analytic tools are all required for high-quality auditing (Cao et al. 2015).

Analytic skills are high in demand, and a variety of position names are used to describe analytic professionals: data scientist, researcher, data analyst, and business analyst (Rexar Analytics 2013). In this study, analytic skills refer to aptitude and proficiency, rather than simply a position name, so the term 'data scientists' refers to analytic professionals in general. Data scientists should have statistical as well as other quantitative and analytical capabilities (Davenport 2014; Davenport & Harris 2007; Dhar 2013; Harris et al. 2013; Harris et al. 2010) such as skills in cleaning and organizing large data sets, and visualization tools and techniques (Harris et al. 2013; McAfee & Brynjolfsson 2012). Harris et al. (2010) mention that four skill sets are required: (i) quantitative and technical skills, (ii) business insights, (iii) relationship and consulting skills, and (iv) expertise in coaching and developing staff.

The range of BDA techniques and software is broad and varied in terms of purpose within a detailed functionality, functional scope, and level of sophistication. Sophisticated analytic tools are required to support decisions by managers and other stakeholders (Chaudhuri et al. 2011; Liu & Vasarhelyi 2014). Furthermore, the quality of analytic tools has a significant impact on data/information quality, managerial decision-making, and organizational performance (Wieder et al. 2012).

How information systems (IS) contribute to organizational performance has long been discussed in the literature. In the Big Data context, IS provides a useful tool that improves the quality of decision-making in the contexts of structured, semi-structured, and unstructured data (Guillemette et al. 2014). By providing new technologies and approaches, BDA supports management decisions with real-time and continuous predictive evidence (Barské-Erdogan 2014; Davenport 2014).

2.3 Data-Driven Decision-Making (DDDM)

A substantial body of research has investigated the antecedents of DDDM and its various impacts on organizational performance. Decision theory in economic science is based on certain assumptions that decision makers are informed, have the capability to calculate, and apply rational procedures to identify all possible alternatives, thereby resulting in optimal decisions (Eilon 1969; Eisenführ et al. 2010; Harrison 1999; Schoemaker 1982). Making sound decisions and putting them into action are attributing of high-performance organizations (Rogers & Blenko 2006). To make high-quality managerial decisions, valid and reliable information, generated from available facts is needed (Rousseau 2006).

3 HYPOTHESIS DEVELOPMENT

BDA can help an organization to better understand its business and market (Chen et al. 2012; Ramakrishna et al. 2011). With new technologies and analytic approaches, BDA can provide managers with real-time planning and continuous forecasting (Barské-Erdogan 2014; Barton & Court 2012; Davenport 2014). BDA generates better information quality for managers. Analytics of a higher volume of data can provide managers with more accurate and reliable information. High velocity of data can supply managers with more timely information. Furthermore, analytics of additional (previously unavailable) and more relevant data can create greater incentive to make managerial decisions based on analytic output. Managers are expected to use BDA to support their decisions if they believe in the quality and usefulness of analytic output. According to DeLone and McLean's IS success model, if managers perceive that analytic output is of greater quality, the possibility that they will use it to support their decisions is higher (DeLone & McLean 1992, 2002, 2003). According to the Technology Acceptance Model (TAM), when managers perceive analytic output as useful, they have greater possibility toward actual use of the analytic output (Davis 1989; Davis et al. 1989; Venkatesh et al. 2003). BDA can have a significant impact on decision-making processes (Kościelniak & Puto 2015), as it can create an opportunity for managers to use analytic output to support their decisions. It is hypothesized that BDA encourages more DDDM. If data analysts are capable of generating high quality analytic outputs, managers are expected to make more of their decisions based on that information provided.

H1: Big Data Analytics leads to more data-driven decision-making.

Higher-quality information can improve the quality of decision-making (Park 2006; Wieder & Ossimitz 2015), which in turn can lead to better organizational performance (Guillemette et al. 2014; Rogers & Blenko 2006). This is supported in economic decision-making theory that when making rational decisions based on information, the decision quality is better (Eilon 1969; Eisenführ et al. 2010; Harrison 1999; Schoemaker 1982). The second hypothesis predicts a positive relationship between DDDM and organizational performance. When managers make data-driven decisions, their decisions will be better and therefore improve organizational performance.

H2: More data-driven decision-making improves organizational performance.

Following to hypothesis 1 and 2, the third hypothesis predicts an indirect effect between BDA and organizational performance via DDDM.

H3: Big Data Analytics improves organizational performance via data-driven decision-making.

BDA can generate benefits to any organization by enhancing organizational performance and competitive advantage (Barton & Court 2012; Liberatore & Luo 2013; McAfee & Brynjolfsson 2012; Moffitt & Vasarhelyi 2013; Schroeck et al. 2012). Organizations have realized the potentially significant value of BDA for operational effectiveness, additional revenue generation, new market development, new product and service offerings, cost savings, and enhanced customer experience (Davenport 2014; Deloitte 2014). BDA can improve decision quality, irrespective of any increases in DDDM. The fourth hypothesis establishes a positive direct effect between BDA and organizational performance.

H4: Big Data Analytics positively impacts organizational performance.

All four hypotheses have been combined to construct an overall research model in figure 1.

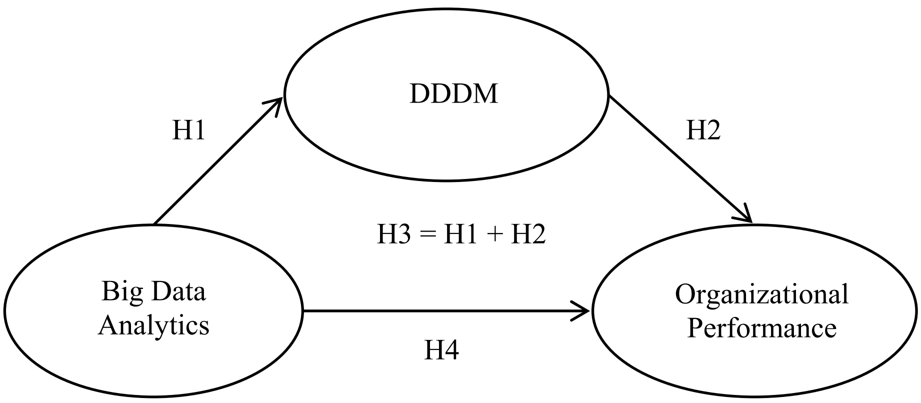

Figure 1. Research Model

4 RESEARCH DESIGN AND METHOD

4.1 Research Design

The proposed research method is a cross-sectional online survey, which is developed based on established and new constructs and measurement instruments. The survey method has been chosen to cover a large target sample.

Questionnaire development partly relied on established constructs and measurement instruments, but for BDA, measurement scales were developed largely based on practitioner literature. The questionnaire design and administration will therefore be conducted in two stages: (1) a constructed scale development survey stage and (2) the hypotheses testing survey stage.

The *face and content validity*, as well as the appropriateness of Likert-type scale endpoints of the survey instrument, were assessed (Podsakoff et al. 2003; Podsakoff et al. 2012). 20 academics and data scientists were chosen, contacted via email, and asked for their feedback. In the validity test invitation email, the objective of the survey was explained. They were invited to assess appropriateness of constructs related to BDA. The assessors' feedback was used to refine the questionnaire.

The survey strategy follows the guidance of Dillman et al. (2009). A mixed mode survey was considered because it can reduce coverage error, improve response rates, reduce nonresponse error, and reduce measurement error (Dillman et al. 2014). However, people have different survey mode preferences (Olson et al. 2012). The target population are individual analysts, who most of the time, work with computer and online medium; therefore, only an Internet-based questionnaire will be used.

The survey will target full-time data science/analytics expert who have worked with their current employer for at least three months. Firm size will be controlled for, so only organizations with more than 50 full-time-equivalent (FTE) employees in any industries will be included in the final sample.

The survey will be conducted in multiple rounds. First, e-mail invitations with a link to the online survey will be sent to target respondents. The first reminder e-mail will be sent two weeks after the initial e-mail to those who have not responded to the survey. The second reminder e-mail will be sent three weeks after the first reminder.

Respondents will be asked to voluntarily provide their organizations' names. Publicly available information of the respondents' organizations will be collected from a database and used for measuring organizational performance. No personal data about the respondents will be collected. *Self-report bias* will be reduced because organizational performance data will be collected both from respondents' perspective as compared to their competitors and from the financial data collected from a database (Podsakoff et al. 2003; Podsakoff et al. 2012). Responses will then be tested for *non-response bias* by comparing early and late responses.

4.2 Construct Measurement

Except organizational performance, each construct specified in the hypotheses is represented as an intangible latent variable (Molloy et al. 2011). The operationalization of the constructs is based on prior literature, but where required, it is developed from practitioner literature.

4.2.1 Big Data Analytics

Big Data Analytics contains two majors components: a) Big Data available to an organization and b) analytic resources of an organization.

a) Big Data is characterized by large 3Vs (volume, variety, and velocity). Respondents will be asked to rate the level of each V in their organization over the past 3 years on a five-point Likert-type scale.

b) Analytic resources exist in two main forms: analytic skills and analytic tools. According to prior literature, there are three analytic skill categories: technical skills, generic skills, and domain knowledge (Accenture 2013; Conway 2010; Davenport & Patil 2012; Harris et al. 2010; McAfee & Brynjolfsson 2012; Minelli et al. 2012; Stubbs 2014; Tambe 2014). Analytic tools refer to methods used in analytics. Respondents will be asked to rate their organizational unit on a seven-point Likert-type scale in terms of the level of their analytic skills and the use of analytic tools.

4.2.2 Data-Driven Decision-Making

Data-driven decision-making refers to whether decisions are based on analytic output and other data. Respondents will be asked to rate the managerial decision style in their organization on a seven-point Likert-type scale.

4.2.3 Organizational Performance

Organizational performance, compared to competitors, refers to four areas: increases in revenues, decreases in cost, increases in market share, and enhancement in profit margins. Respondents will be asked to rate their organizational performance, relative to their competitors or benchmark organizations, in the past 12 months, on a seven-point Likert-type scale.

4.3 Analysis Method

Data will be analysed using contemporary data analysis techniques and tools (for example, PLS-SEM with Smart PLS, SPSS). The PLS procedures will be used to test the path model and hypotheses. PLS is appropriate for non-normal distribution and small sample size studies and is suitable for indirect effect analysis in multi-mediator models (Gefen & Straub 2005). 'SmartPLS' version 3 (Ringle et al. 2005) will be used for the PLS analysis. All constructs in the PLS model will be tested for convergent and discriminant validity (indicators and constructs) (Hulland 1999). The bootstrapping approach will be applied as the resampling technique to estimate the significance of the paths. Construct loadings will be calculated to assess their significance. A path model will then be estimated to show hypothesized direct and indirect effects.

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