IF KNOWLEDGE IS POWER, THEN BIG DATA RULES: WHO RESISTS THE ANALYTICS REVOLUTION AND WHAT LIMITS ORGANIZATIONAL PERFORMANCE?

by

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A Dissertation Presented in Fulfillment of the Requirements for the Degree

Doctor of Philosophy in Marketing and Management

Faculty of Business and Economics

Macquarie University

September 2016

THESIS CERTIFICATION

I, Chu Wang, declare that this thesis, submitted in fulfilment of the requirement for the award of Doctor of Philosophy in Marketing and Management, Macquarie University, is wholly my own work unless otherwise referenced or acknowledged. The data were collected by interviews and questionnaires. Ethics Committee approvals have been obtained (Reference numbers: 5201300405 and 5201300692). This document has not been submitted to any other academic institution for qualifications.

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ABSTRACT

Big data has been widely recognized as a critical source of competitive advantage (Manyika, Chui, Brown, Bughin, Dobbs, Roxburgh and Byers 2011). Studies show that big data-driven decisions lead to 5 to 6 percent increase in profitability (Barton and Court 2012; Brown, Chui and Manyika 2011; McAfee, Brynjolfsson, Davenport, Patil and Barton 2012). Therefore, “knowledge is power” in the sense that big data analytics provide the insights to increase organizational performance. However, few studies show how to motivate employees to become data driven and how organizations achieve excellent data analytics performance.

This research comprises three studies. Study 1 examines how organizational contexts and analytics attributes interact and affect analytics adoption behaviors. Data were obtained from 337 big data marketing professionals. Findings show that contextual factors (i.e. centralization and politics) have varying impacts on the relationships between individuals’ acceptance of big data and big data attributes. Specifically, intentions to adopt big data during the pre-adoption period were contingent on contextual factors, whereas the actual usage was dependent on individuals’ assessments of big data, rather than organizational contexts.

Study 2 takes a social perspective to examine how relationships with big data consulting firms affect three sequential steps of big data innovation process (i.e. adoption, diffusion and implementation). Questionnaires were obtained from 188 potential adopters and 149 big data users. Results show that social capital from consulting firms have insignificant effects on individuals’ intentions to adopt big data but have facilitating effects on individuals’ intentions to use and even stronger effects on actual usage of big data. That is, consultants primarily support the technical execution of big data analytics, rather than a firm’s decision to adopt the big data approach in the first place.

The purpose of Study 3 is to address how to achieve high-level of big data performance. This study establishes a strategy-execution-performance framework and tests this framework with a unique dataset, which includes matched pairs containing 200 internal assessments from employees of 16 organizations and 78 external assessments of performance from 15 big data consultants. Results show that 55 percent variance of big data performance is explained by execution process variables. Results also indicate that execution process is significantly correlated with organizational strategic responsiveness.

The findings contribute to the theory development on data analytics, and to analytics practice, where leaders seek to transform and motivate employees to become data-driven, and to improve data analytics performance.

ACKNOWLEDGEMENTS

I would like to express my deepest gratitude to Prof. Scott Koslow for his full supports, excellent guidance and encouragement during the doctoral research journey. Scott, thank you for telling me the beauty of wondering in the dark, for showing me what the high-level research should be, and for always pushing me to a higher-level. Without your full supports, patient guidance and your wisdom, the journey would have been dreadful and devastating.

I would also like to express my sincere gratitude to Prof. Mark Gabbott for his expert guidance, and encouragement during the doctoral study. Without his guidance and persistent supports, the data collection process would have been frustrating, and the thesis would not have been possible.

I would also like to express my sincere gratitude to Prof. Guijun Li for his continuous supports and inspiring guidance during my academic journey. Without his guidance and encouragement, the doctoral study would not have become a reality.

I would also like to thank Prof. Lorne Cummings, Ms. Agnieszka Baginska, Ms. Lin Bai, Ms. Yanru Ouyang, Mr. James Keene, Ms. Megan Nixon and Mr. Ed Dharmadji for their supports and helps during the doctoral study.

My sincere gratitude also goes to those data scientists and my research colleagues, especially dear Kagiso and Jenny who have helped, supported, encouraged and inspired me throughout my doctoral research journey.

To my parents and husband, thank you for supporting me throughout the research journey. Love you all.

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CHAPTER 1: INTRODUCTION

This research investigated the factors that affect big data innovation at both individual and organizational levels. Big data has been recognized as a critical source of competitive advantage (Manyika et al. 2011). To seize the potential of big data and achieve new competitive growth have been considered as top priorities (Barton and Court 2012; Bughin et al. 2011; McAfee and Brynjolfsson 2012). However, an issue is that many organizations have invested a massive amount of money into big data technologies, but not yet generated real business value from big data (Bughin et al. 2011; Davenport et al. 2001; McAfee and Brynjolfsson 2012). The purpose of this research was to help organizations and managers to understand the mechanism of big data adoption and performance and seize the potential of big data.

In this chapter, research background, the problem and research purpose, together with the theoretical and managerial significance of the research are discussed. Additionally, the three studies of this doctoral research are introduced, including research questions, theoretical framework and the research design. At the end of this chapter, a summary is presented.

Background

Technological upheaval in the past decade has resulted in the unprecedented data explosion (Brown et al. 2011). Enormous data are generated and stored every day. Shopping offline, individuals generate massive scanner data (Brown et al. 2011). Browsing web pages, individuals leave reams of clickstreams data (McAfee and Brynjolfsson 2012). Using smartphones and other smart mobile devices such as tablets, individuals produce real-time location data (Manyika et al. 2011). Even those wearable technologies, such as Fitbit, have generated a huge amount of real-time exercise and health data.

Organizations have witnessed the game-changing influence of big data (Brown et al. 2011). Online retailers can predict customer preference by analyzing clickstreams and display the recommended products at the right position, which cannot be done by offline retailers

(McAfee and Brynjolfsson 2012). Moreover, organizations can measure public sentiment through analyzing social media data and actively optimize marketing strategy accordingly (Bughin et al. 2011). Big data is like the real-time diary of each customer, which enables organizations to understand customer preference and predict customer behaviors more precisely. Researchers have predicted that big data will become a strategic asset, without which organizations would not survive the competition (Bughin et al. 2011; Manyika et al. 2011).

As a result, increasingly more organizations have put big data on the top of organizational agenda (Bughin et al. 2011). In the United States, online retailers such as Amazon have built advanced recommendation system based on the massive clickstream data, and technology giants such as Facebook and IBM have built an alliance to capitalize on big data (McAfee and Brynjolfsson 2012; Pressman 2015). In Australia, Woolworths have invested 20 million dollars to get 50 percent shares in Quantium, a big data analytics company (Ruehl 2013). Coles, the major competitor of Woolworths, also built a FlyBuys program and launched a corresponding fee-free credit card in an attempt to track customers' habits and achieve competitive success (Ruehl 2013). Australian retailers are not alone in the big data innovation path. National Australian Bank has decided to turn big data into customer insights, based on which financial products and services would be recommended to customers (Head 2013). Other big banks, such as Commonwealth Bank and Westpac Bank, have also put significant emphases on big data analytics (Eyers 2014; Head 2013; Ramli 2013).

Despite massive investments in big data innovation and data scientists, organizations have had somehow mixed performance, with only a few have generated real business value from big data. Not many organizations with massive investments in big data have seen improved customer satisfaction, a larger market share or higher profits[1]. The failure in turning data into valuable results could be resulted from inappropriate organizational contexts,

[1] In Study 3 (Chapter 4), we compared the customer satisfaction index, normalized profits and market share of major big data adopters in Australia during both pre- and post-adoption period. More than half of these companies have not seen improved performance after big data adoption.

unsatisfactory expertise and capabilities, or antiquated decision process (Barton and Court 2012; Brown et al. 2011; Davenport 2001). As a response to the gap between big data inputs and outputs, this research aimed to discover the factors affect big data adoption and performance.

Many researchers have attempted to explain how organizations can succeed in data analytics (e.g. Barton and Court 2012; Brown et al. 2011; Bughin et al. 2011; Davenport 2006; Davenport et al. 2001; Manyika et al. 2011; Mayer-Schönberger and Cukier 2013; McAfee and Brynjolfsson 2012). These studies on data analytics discussed a broad range of factors that might be related to data analytics performance. These factors were ranging from capabilities to organizational culture, from strategy to execution, and from individual level to organizational level, and so forth. The relations between these factors presented in the data analytics literature and data analytics performance are somewhat confusing and inconclusive, making it even more difficult to know which factors are essential and effective. Moreover, existing literature are mainly based on qualitative analysis, whereas the use of quantitative methods is rather limited. The statistical investigation in our research not only enriched data analytics theories but is also a complementary method that provides cross-validation to existing qualitative findings.

For example, McAfee and Brynjolfsson (2012) suggested that organizations with the transitions to use big data should carefully consider five factors. The five factors were leadership, talent management, technology, decision-making and organizational culture. Earlier, Bughin, Livingston and Marwaha (2011) gave a similar suggestion that leadership, talents, technology were the main factors to consider if organizations attempt to exploit big data analytics. Both studies were based on qualitative analysis.

Davenport, Harris, De Long and Jacobson (2001) established a data-to-result model based on interviews and case studies. They suggested that analytical outcomes were affected by two categories of factors, one being contextual factors and the other being transformation process. Concretely, contextual factors were the strategy, skills and experience, organizational culture, and technology and data, whereas the transformation factors were analytical process and decision process. In a later study, Davenport (2006) identified four shared characteristics of successful analytical companies through the study of 32 companies. The four common characteristics were the right focus, the right culture, the right people and the right technology. To compete on analytics, organizations require not only employees with the right expertise and willingness to use analytics, but also leaders with strong commitment and willingness to create the right strategy and culture for data analytics. Some other studies also showed that strategy, people, and culture were key success factors of data analytics (e.g. Barton and Court 2012; Brown et al. 2011). The majority of these studies were based on qualitative analysis.

Data analytics researchers emphasized that people be important factors in data analytics (e.g. Barton and Court 2012; Davenport et al. 2001), but few have discussed what affect individual willingness to use data analytics. Moreover, the relationships between factors presented in the above literature (e.g. Barton and Court 2012; Brown et al. 2011; Bughin et al. 2011; Davenport 2006; Davenport et al. 2001; McAfee and Brynjolfsson 2012) and data analytics success have not been examined with statistical analysis yet. The two limitations in the literature, together with the below-expectation big data performance in Australia, shaped our primary motivation for this doctoral research. In this research, factors affecting individual adoption and usage of big data, as well as those affecting big data performance at the organizational level were explored and tested.

The Problem

Generally speaking, the empirical problem is that not many organizations have successfully turned big data into valuable results. Over recent decades, more and more organizations have turned to big data analytics to obtain customer insights to improve competitive advantages. But not many organizations understand how to proceed big data analytics (Barton and Court 2012) and even less have derived valuable results from big data (McAfee and Brynjolfsson 2012). While success in big data analytics can result in larger market share, greater operation efficiency or higher profitability (Manyika et al. 2011), inefficient adoption and usage of big data means a waste of billions of dollars or even the breakdown of strategy and operation. It is crucial to understand the key success factor for big data analytics. Organizations tend to proceed big data innovation by investing massively in technology, yet data analytics literature have demonstrated that these investments do not secure positive outcomes (Davenport 2006; Davenport et al. 2001). The more important factors are people, organizational contexts and even the partnership with technology leaders such as IBM and Hewlett-Packard (e.g. Barton and Court 2012; Brown et al. 2011; Davenport 2006; Davenport et al. 2001; Manyika et al. 2011; McAfee and Brynjolfsson 2012).

Specifically speaking, the problem is twofold. Firstly, to seize the potential of big data, organizations should understand which factor motivates employees to become data-driven. Second, to succeed in turning big data into valuable results, organizations should understand what the key success factors are. In this research, face-to-face interviews and questionnaires were used to obtain information from big data users and potential adopters. We examined the effects of big data attributes, organization contexts and social capital (i.e. consulting firms) on individual adoption and usage of big data, and this examination was presented in Study 1 and Study 2. We also explored and tested the key success factors of big data at the organizational level, which was presented in Study 3. Organizational leaders and data analysts could gain insights into motivators of big data usage at the individual level, as well as key success factors of big data performance at the organizational level.

Research Purpose

The purpose of this quantitative research was to examine which factor affect big data adoption and usage at the individual level, and investigate which factor affect big data performance at the organizational level. Specifically, three studies were conducted. In the first study, the effects of organizational contexts and big data attributes on individual willingness to adopt and use big data were examined. To collect data for statistical analysis, online questionnaires were listed on two big data related websites. By testing the influences of organizational contexts and big data attributes on individual acceptance of big data, the main object of Study 1 was to add to the literature by linking individual acceptance of information technology theories and situational theory and show how big data adoption behaviors at the individual level are contingent on organizational contexts. Study 1 also aimed to guide organizational leaders to create an appropriate organizational context, in which employees are more willing to become data-driven.

The purpose of the second study was to show the effects of social capital (i.e. consulting firms) on individual big data adoption behaviors. Increasing organizations have built partnerships with consulting firms to exploit big data (Pressman 2015). By examining the effects of consulting firms on big data analytics during three sequential stages (i.e. adoption, diffusion and implementation), the object of this study was to guide organizational leaders to source external expertise and manage the interactions with external consulting firms. Study 2 also added to the literature by linking social capital theory and individual acceptance of information technology theory, and illustrating the varying roles of social capital on different stages of big data innovation.

The purpose of the third study was to investigate the factors underpin big data performance at the organizational level. To obtain data for statistical analysis, questionnaires were sent to executives, data scientists, other data-related employees, as well as analytics consultants. This study filled the void in the literature by establishing a model to explain data analytics performance. This study also aimed to provide an empirical guide for organizational leaders to achieve valuable outcomes from big data analytics.

Significance of the Research

Both researchers and practitioners have recognized the strategic importance of data analytics (Brown et al. 2011; Davenport 2006; Davenport et al. 2001; Manyika et al. 2011; McAfee and Brynjolfsson 2012). Despite the increasing research into data analytics during the past decades, no real theory has emerged to explain data analytics performance. For example, studies on scanner data analytics mainly focus on the technical aspects, and few have shown how organizations could achieve better data analytics performance (Bucklin and Gupta 1999). Moreover, prior studies were heavily relying on qualitative methods, with few had used statistical analysis to support the examinations. McAfee and Brynjolfsson (2012) suggested five factors for big data innovation, leadership, talent management, technology, decision-making process and organizational culture. Davenport (2006) identified four common features of successful analytical companies, the right focus, the right culture, the right people and the right technology. These studies were based qualitative analysis and provided little statistical evidence. The factors presented in the existing literature were from a broad range, making it difficult to understand which factors are most relevant and effective. These limitations call for more systematic, valid and reliable quantitative investigations on data analytics innovation and performance.

This doctoral research was a comprehensive investigation of big data analytics at both individual and organizational level. Factors, which affect big data adoption and usage at the individual level, were organized into three categories, organizational contexts, innovation attributes and social capital. Factors, which influence big data performance at the organizational level, were classified into organizational contexts and decision process. By examining how analytics attributes, organizational contextual factors and social capital interact and affect big data analytics innovation at both individual and organizational level, this research provides a holistic picture of data analytics that could contribute to further theory development and provides the empirical guide to data analytics management.

This research was imperative to practitioners for three reasons. Firstly, big data has been recognized as a strategic asset, which has generated great opportunities for practitioners to gain deeper insights into customer habits and achieve higher value (Manyika et al. 2011). Secondly, the rapid-growing data and the increasing big data adoptions by competitors have put intense pressure on organizational leaders, who in turn have to exploit big data and generate valuable outcomes (Brown et al. 2011). Lastly, many organizations are not ready for big data analytics because the technical and managerial challenges of big data innovation are big and real (McAfee and Brynjolfsson 2012), and leaders are not sure where to start and how to proceed (Barton and Court 2012). This research helps leaders and other practitioners to gain comprehensive insights into how to achieve higher big data performance at the organizational level, and how to motivate individuals to become data-driven.

Conventional managers make decisions based on intuition, which is shaped through experience (McAfee and Brynjolfsson 2012). One possible reason is that data are scarce, and are challenging and expensive to collect and analyze (McAfee and Brynjolfsson 2012). The new technology revolution has made data much easily accessible, and organizations now can collect a massive amount of data to create customer knowledge (Manyika et al. 2011). Leaders can and should develop capabilities to overcome technical and managerial challenges and generate value from big data analytics. By examining the effects of organizational contextual factors and social capital, this research provides guidance to organizational leaders on how to build an appropriate organizational context and exploit social capital in attempt to improve big data performance and motivate employees.

To exploit big data, many organizations have spent a massive amount of money on big data warehouse, analytical and visualization tools, and numerous other technologies, as well as talented data scientists, without understand that the managerial changes are much more urgent than the technology improvement (McAfee and Brynjolfsson 2012). Implementing new systems without building a supportive organizational context and corresponding managerial practices, organizations might achieve low value from data analytics. The failure of ERP data and customer data analytics presented in the study of Davenport et al. (2001) well exemplified the importance of managerial changes. In the book *the fifth discipline: The art & practice of the learning organization*, Senge (2006) alerted organizational executives to the risks of symptomatic solutions, which can clear the symptoms but cannot solve the problem. To solve the problem, leaders should find out the root cause. This view is very similar to the principle of Chinese medicine science that doctor should address both symptoms and root cause to heal patients. Treating symptoms without the diagnosis of root cause might result in palindromia. This research aimed to guide organizational leaders to understand the root cause of poor big data performance and solve empirical problems in big data implementation process. Based on face-to-face interviews and statistical analysis, this research also provides reliable evidence for empirical data analytics management.

Research Questions

Data analytics researchers have emphasised that it is imperative for leaders to motivate employees to become data driven (e.g. Barton and Court 2012; Davenport 2006; Davenport et al. 2001; McAfee and Brynjolfsson 2012). Employees' unwillingness to use big data, which is resulted from the lack of trust and capabilities, ends up with the poor organizational implementation of big data (Barton and Court 2012). To seize the potential of big data, organizations should understand how to motivate employees to become data-driven. Venkatesh et al. (2003) compared eight competing models of individual acceptance of information technology and showed that Rogers' (1995) innovation diffusion theory had the strongest predictive power. According to innovation diffusion theory (Rogers 1995), innovation adoption can be predicted by five innovation attributes, namely relative advantage, complexity, compatibility, trialability, and observability. The relation between innovation attributes and individual adoption behaviors might be contingent on organizational contexts. Situational theorists suggested that the expectation and vision shared within the same context might reshape individuals' perception and behaviors (Meyer, Dalal and Hermida 2010). In the first study, the research question was: how do big data attributes and organizational contextual factors interact and affect individual adoptions and usage of big data?

The prevalence of partnership with consulting firms (Pressman 2015) has raised a question on the roles of consulting firms in big data innovation. However, there were few studies on the relationship between consulting firms and big data analytics. This void has led to the research question in the second study of this research: how do consulting firms affect the adoption and usage of big data?

A few qualitative studies have attempted to discover the key success factors of data analytics (e.g. Barton and Court 2012; Brown et al. 2011; Bughin et al. 2011; Davenport 2006; Davenport et al. 2001; Manyika et al. 2011; McAfee and Brynjolfsson 2012). However, few quantitative analyzes were conducted to explain data analytics performance. Davenport et al. (2001) developed a data-to-result model and suggested that organizational contexts and transformation process were imperative to data analytics outcomes. However, few empirical investigations have been conducted to examine this view. This limitation in the literature has led to the research question in the third study: how do organizational contexts and transformation process affect big data analytics performance?

Conceptual Framework

The conceptual framework of the first study was mainly based on three streams of theories, which were individual acceptance of information technology theories, Rogers' (1995) innovation diffusion theory and situational theory.

Extensive research has been conducted to explain individual acceptance of information technology (e.g. Agarwal and Prasad 1997; Ajzen 1991; Davis 1989; Davis, Bagozzi and Warshaw 1989 & 1992; Mathieson 1991; Plouffe, Hulland and Vandenbosch 2001; Venkatesh et al. 2003). There are several competing theories, mainly including the theory of reasoned action (Davis et al. 1989), the technology acceptance model (Davis 1989), the motivational model (Davis et al. 1992), the theory of planned behavior (Mathieson 1991) and innovation diffusion theory (Plouffe et al. 2001; Rogers 1995). Venkatesh et al. (2003) compared these competing models and found that Rogers' innovation diffusion theory had relatively strong predictive power.

Innovation Diffusion Theory was originated from sociology and has been applied to investigate a broad range of innovations (Rogers 1995; Venkatesh et al. 2003). According to the innovation diffusion theory, the adoption of innovations is determined by the individual perception of the innovation characteristics, including relative advantage, compatibility, complexity, trialability and observability. These five attributes can explain 49 to 87 percent of the variance of the adoption rate of innovation (Rogers 1995).

Despite the vast acceptance of innovation diffusion theory, some researchers argued that the relationships between innovation attributes and adoption behaviors were contingent on organizational settings (e.g. Venkatesh et al. 2003). For example, Venkatesh et al. (2003) demonstrated that the effects of innovation attributes in mandatory settings were different from those in voluntary settings. These findings can be explained by the situational theory. The essence of the situational theory is that individuals are constrained by situational strength (e.g. Adkins and Naumann 2001; Bacharach and Bamberger 2007; Meyer et al. 2010). By reviewing the literature on situational strength, Meyer et al. (2010) concluded that the situational strength could be operationalized into four facets, namely constrains, consequences, clarity and consistency. They also suggested that researchers might consider including contextual factors to address situational strength.

Based on the above three streams of literature, the approach to address the first research question was developed. Following individual acceptance of information theory (e.g. Davis et al. 1992), individual acceptance of big data was operationalized into three variables, including the individual intention to adopt big data during the pre-adoption period, intention to use big data during the post-adoption period and the actual usage of big data. The independent variables included innovation attributes from innovation diffusion theory (e.g. Rogers 1995; Venkatesh et al. 2003), as well as organizational contextual factors from the literature on situational theory (e.g. Adkins and Naumann 2001; Bacharach and Bamberger 2007; Meyer et al. 2010). Five big data innovation attributes including relative advantage, complexity, compatibility, trialability and observability, together with three organizational contextual factors including strategic responsiveness, centralization and politics, were examined in the first study.

The conceptual framework of the second study was based on three streams of theories. Two of them were individual acceptance of information technology theory and innovation diffusion theory, similar to the first study. The rest one was the social capital theory.

Social capital theory concerns about how resources embedded within social networks affect network actors' behaviors and performance (Nahapie and Ghoshal 1998). Introduced from sociology, social capital theory is gaining popularity in marketing and management literature over the past two decades. The burgeoning literature shows that social capital, which provides access to information and knowledge, skills and capabilities, new customers and markets and other valuable relational resources, might produce significant effects on marketing performance and even firm value creation (e.g. Atuahene-Gima and Murray 2007; Luo, Griffith, Liu and Shi 2004; Nahapie and Ghoshal 1998; Pérez-Luño et al. 2011).

To understand how consulting firms affect individual big data adoption behaviors, we addressed the second research question from a social capital perspective. The social capital derived from relationships with consulting firms, such as information and knowledge, were defined as consulting assets. Based on social capital theory, the effects of consulting assets on individual intention to adopt and use big data and actual usage of big data were examined in the second study.

The third study aimed to examine which factor underpins big data performance. A few researchers have attempted to examine key success factors of data analytics performance (e.g. Barton and Court 2012; Brown et al. 2011; Bughin et al. 2011; Davenport 2006; Davenport et al. 2001; McAfee and Brynjolfsson 2012). However, no real theory has emerged to explain data analytics performance except for the data-to-result model established by Davenport et al. (2001). Based on interviews with analytical firms, Davenport et al. (2001) suggested that monetary investments could not guarantee analytics performance. To achieve high analytics performance, organizations require appropriate contexts and the right transformation process. Little quantitative analysis has been conducted to examine this model.

Based on the data-to-result model (Davenport et al. 2001), we proposed and examined a strategy-execution-performance framework to explain big data performance in the third study. Based on data analytics literature (e.g. Barton and Court 2012; Brown et al. 2011; Davenport 2006; Davenport et al. 2001; McAfee and Brynjolfsson 2012), contextual factors in the third study were strategic responsiveness, centralization and competition intensity. The factors of execution process were from both data analytics literature (e.g. Davenport et al. 2001) and decision process literature (e.g. Ketchen, Snow and Street 2004; Priem, Rasheed and Kotulic 1995). Execution process was captured through two factors, evaluation of big data and big data-driven decision. Figure 1.1 shows the conceptual framework of this research.

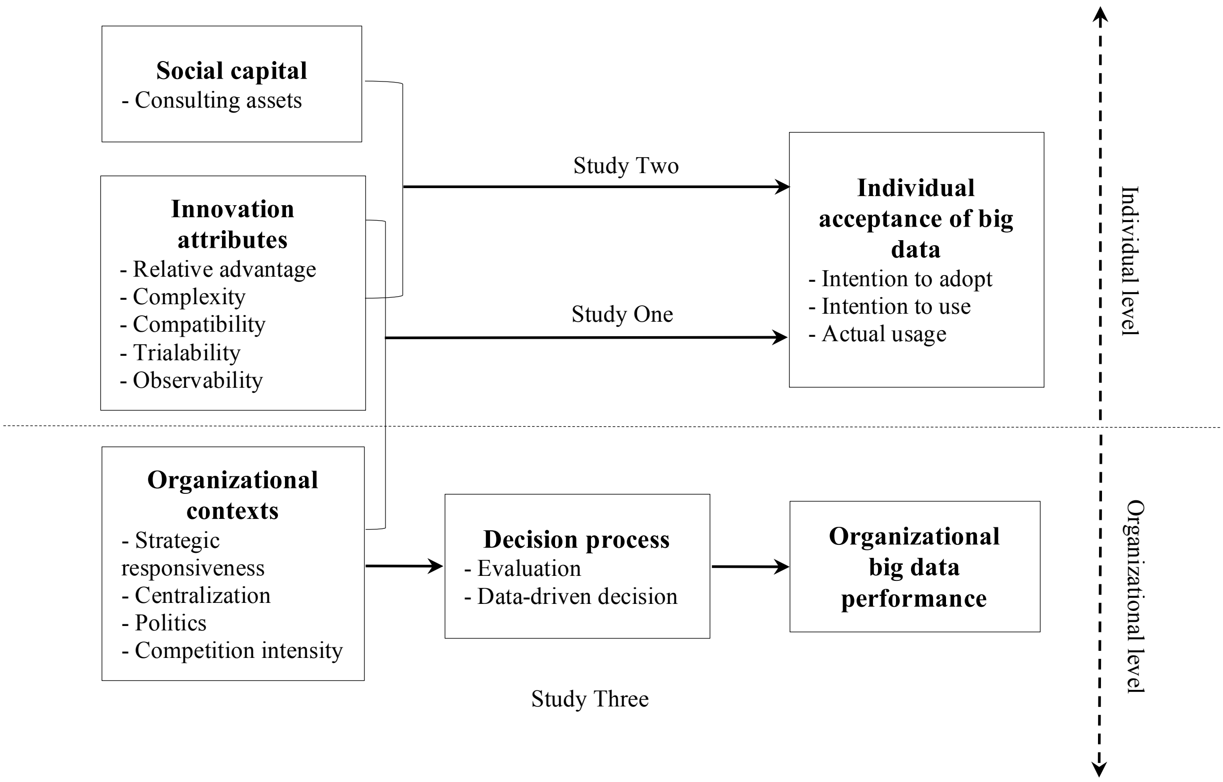

Figure 1.1 The conceptual framework of the thesis

Terms and Definitions

This section provides definitions for the major terms that are constantly used in this thesis. The following description contains common definitions in existing literature and the adapted definitions for the present research context.

Big data: According to the *Compact Oxford English Dictionary of Current English*, data refer to facts and statistics collected together for reference or analysis. Data as an abstract concept can be viewed as the lowest level of abstraction from which information and then knowledge are derived. Big Data describes the exponential growth and availability of data that are generated from transactional system, mobile devices, web clickstreams, machine sensors, and virtually anything that generates an electrical pulse, or could be purchased from external third party. The distinctive features of big data are its high volume, high velocity and high variety, which make it difficult to be processed by traditional systems (Manyika et al. 2011; McAfee and Brynjolfsson 2012).

Individual acceptance of big data: Individual acceptance of information technology refers to the degree to which users intend to use and/or actually use certain information technology (Davis 1989; Davis et al. 1989 & 1992; Venkatesh et al. 2003). In this thesis, individual acceptance of big data was captured by individual intention to adopt/use big data, as well as the actual usage of big data. In Study 1 and 2, individual acceptance of big data was treated as dependent variable in an attempt to examine how organizational contexts, big data attributes and social capital affects big data adoption behaviors.

Big data performance: Davenport et al. (2001) stated that the data analytics outcomes include changes in behaviors, process and programs, and financial results. In this research, big data performance refers to the degree to which organizations have turned big data into valuable outcomes.

Strategic responsiveness: Strategic responsiveness refers to the extent to which an organization can proactively adapt its strategy to the changing environment. Being strategic responsive, organizations should actively track market trends to seize new opportunities and avoid potential threats (Haleblian and Finkelstein 1993; Moorman 1995).

Centralization: Centralization is the major construct of organizational structure. Centralization captures the degree to which the power is consolidated under a central control (Davenport et al. 2001; Deshpande 1982; Deshpande and Zaltman 1982).

Organizational politics: Based on the literature of politics (e.g. Eisenhardt and Bourgeois 1988; Gandz and Murray 1980), we define politics as those deliberate behaviors that are often conducted in a devious and underhanded way with attempts to achieve self-interests, which conflict with some other individuals' and might, but not always, harm organizational effectiveness.

Competition intensity: Competition intensity measures the degree to which competition environment changes, such as the threats of potential new entrants and the destructive power of competitors' moves (Moorman 1995).

Big data attributes: Following Rogers' innovation diffusion theory (1995), big data attributes contained relative advantage, complexity, compatibility, trialability and observability. *Relative advantage* refers to the degree to which big data is better than traditional datasets. Relative advantage can be economic returns, low costs, social prestige, and the saving in time and/or effort, and so forth (Rogers 1995). *Complexity (*e.g. the reversal of *ease of use)* refers to the degree to which big data is perceived as relatively difficult to understand and use. *Compatibility (i.e. information seeking)* refers to the degree to which big data is perceived as compatible with current work. *Trialability* refers to the degree to which big data can be experimented on a limited scale. *Observability* refers to the degree to which the application and the outcomes of big data are visible to others.

Social capital: Scholars have attempted to elaborate social capital into various disciplines to explain a wide range of social behaviors. The majority of researchers defined social capital by its effects, including resources derived from certain networks (e.g. Baker 1990; Lin 1999; Nahapiet and Ghoshal 1998), and function of facilitating certain actions (Coleman 1988). Following Nahapiet and Ghoshal (1998: pp 243), social capital was defined in this research as "the sum of the actual and potential resources embedded within, available through, and derived from the network of relationships possessed by an individual or social unit".

Consulting assets: Following Nahapiet and Ghoshal's (1998) definition of social capital, we defined consulting assets as the resources embedded within, available through and derived from the relationships with consulting firms.

Summary

Big data has become the frontier of innovation and competitive advantage (Manyika et al. 2011). Turning big data into valuable results has become the top priority of increasingly more organizations (e.g. Eyers 2014; McAfee and Brynjolfsson 2012; Pressman 2015; Ruehl 2013). This chapter provided a general introduction to this thesis, which attempted to examine how to motivate individuals to become data driven and which factor affect big data performance at the organizational level. The first study examined how organizational contexts and big data attributes interact and affect individual acceptance of big data. The second study examined how consulting assets affect individual acceptance of big data. These two studies could guide leaders to motivate individuals to become data-driven. The third study built a strategy-execution-performance model to explain big data performance at the organizational level, which showed the root cause of poor big data performance. The conceptual framework of this research was based on the individual acceptance of information technology theory (e.g. Davis 1989; Davis et al. 1989 & 1992; Venkatesh et al. 2003), innovation diffusion theory (Rogers 1995), situational theory (e.g. Adkins and Naumann 2001; Bacharach and Bamberger 2007; Meyer et al. 2010), social capital theory (e.g. Nahapie and Ghoshal 1998), and the data-to-result model (Davenport et al. 2001). Definitions of the repeatedly used terms were defined.

In Chapter 2 to 4, the three studies of this research were presented. Chapter 5 presented an overall conclusion of this research. Implications, limitations and future research were also discussed in Chapter 5.

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CHAPTER 2: WHAT IS THE BIG DEAL WITH BIG DATA? BUILDING ABSORPTIVE CAPACITY WITH MARKETING ANALYTICS INNOVATION

Abstract

Extensive research has contributed to the technical improvement in marketing analytics, but how is marketing analytics diffused to marketers? This paper established PLS models to predict both individuals' intentions to adopt big data analytics and their actual usage. We adapted big data attributes from Rogers' (1995) innovation diffusion theory and also incorporated contextual factors from absorptive capacity research, including organizational politics and centralization. A sample of 337 marketing professionals was collected to test the framework. Results showed that contextual factors had significant effects on individuals' intentions to adopt big data during the pre-adoption period, but had insignificant ones during the post-adoption period. That is, contextual factors' effects vanished after the organizational adoption. Results also showed the contrasting effects of centralization and organizational politics on big data innovation. The study contributes to the big data analytics research by demonstrating when and how contextual factors and big data attributes affect individuals' acceptance of big data.

Introduction

The efficient deployment of data analytics is an established source of organizational competitive advantage (Davenport 2006; Davenport and Harris 2007; Davenport et al. 2001). Innovations in marketing analytics to extract insights from data have always been pivotal in marketing decision-making (Davenport et al. 2007). Correspondingly, extensive research has focused on the improvement of methods and tools to extract insights from data to support marketing decision-making (Bucklin and Gupta 1999; Cui and Wang 2010).

Although there is value in big data and the analytic systems that support it, other research asks why some firms embrace it, but others do not. For example, some studies investigate factors influencing managers' use of market research (Deshpande 1982; Deshpande and Zaltman 1982), and others directly investigate marketers' intention to adopt marketing analytics. Venkatesh et al. (2003) point out that Rogers' innovation characteristics explain more variance of individual acceptance of information technology compared to factors in other competing models. One can look at big data analytics as an innovation that diffuses among firms, and the critical causal factors may be innovation-oriented ones.

However, using big data analytics is unlike other innovations in that it can also guide firm strategy—and another theoretical perspective may view it as building absorptive capacity so that firms can identify and assimilate new knowledge about their markets (Cohen and Levinthal 1990). A big data approach is not a relatively costless adoption decision where one takes advantage of a readily available public good. That is, it is not like a radio broadcast that anyone can access and enjoy by turning on radio. Instead, significant organizational effort has to be undertaken, and implementation impediments have to be overcome. Thus, more strategic management-flavored contextual factors may also influence how firms use big data analytics.

A common factor studied in the strategic management literature, centralization, may be relevant as well. Studies have shown that centralization influences managers' use of market research (Deshpande 1982; Deshpande and Zaltman 1982). Surprisingly, however, more centralization seems to reduce knowledge performance (Pertusa-Ortega, Zaragoza-Sáez, and Claver-Cortés 2010) and exploratory innovation (Jansen, Van Den Bosch and Volberda 2006)—yet a centralized big data department is a common way firms choose to build big data capacity.

Also, organizational politics may also be a relevant causal factor in that politics often works by restricting information so to influence individuals' attitudes and the organization decision process (Eisenhardt and Bourgeois 1988). If a firm takes a big data approach, then analysts have the ability to circumvent the political process and find key pieces of information relevant to decisions.

We propose to integrate the strategic approach to big data and the innovation approach, with a special focus on interactions between the two sets of factors. We note that when contextual factors are strong, individuals' behaviors tend to be influenced more by the expectations shared within the same contexts (Meyer, Dalal and Hermida 2010) and thus organizational contexts may moderate how innovation characteristics influence adoption. Depending on where managers are in their journey to use big data—whether at the stage of pre-adoption intention to adopt, or post-adoption actual use—different interactions will be expected.

This study develops a PLS model to understand how the two major forces (i.e. strategic context and analytics' innovation characteristics) shaping individuals' intentions to adopt big data during the pre-adoption and the actual usage of analytics. The data come from two groups of analytics professionals. There were 337 respondents total for a response rate of 19 percent. All respondents reported on their organizations during the pre-adoption phase, and a subset of 149 respondents also reported on their organizations during the post-adoption phase.

Overall, we show the complex dynamics of big data in that some strategic factors like centralization may strengthen the effect of trialability on adoption intentions, but hinder that of relative advantage. Contrastingly, politics may suppress the effect of trialability, but amplify the importance of relative advantage for adoptions. However, to set the stage for the theory, first Roger's theory will be reviewed, and then strategic approach introduced.

Theory Development

Instead of generalizing the effects of innovation attributes and the contextual factors, the literature review focuses on when and how these factors are effective. Firstly, we review the literature on the relationship between Rogers' innovation attributes (i.e. relative advantage, complexity, compatibility, trialability and observability) and individual acceptance of innovation. The focus is on which stage of adoption process each innovation attribute is effective and why. Secondly, we review the effects of two contextual factors (i.e. organizational politics and centralization). The focus is on how these contextual factors interact with each innovation attributes and how the interactions change over time. Thirdly, we also examine how individual acceptance of big data affects organizational big data performance. Hypotheses are developed along the literature review in this section.

Individual acceptance as the outcome

Individual acceptance has been a critical indicator of innovation adoption and assimilation (Agarwal and Prasad 1997). Without individual acceptance, organizational investments on innovations are not likely to increase productivity (Agarwal and Prasad 1997). That is, to realize expected gains of innovation, the innovation must be accepted and implemented by target individuals.

We focus on two outcomes that have dominated the studies in individual acceptance of information technology. These outcomes are adoption intentions during the pre-adoption period (e.g. Karahanna et al. 1999), and actual usage during the post-adoption period (e.g. Agarwal and Prasad 1997). Firstly, adoption intention captures one's internal willingness and plan to adopt an innovation. Adoption intention reflects the very initial individual acceptance during the pre-adoption period and also the likelihood that the innovation will be adopted. It allows us to examine the effects of innovation attributes and contextual factors during the pre-adoption period. Secondly, current usage is a measure of innovation implementation. It signals that adopters have gone through the behavior modification process and become actual users (Agarwal and Prasad 1997).

Application of attributes to big data: Summary of effects

Relative advantage. The salience of relative advantage has been shown in the majority of literature on individual acceptance of technology. For example, in a meta-analysis of innovation attributes research, Tornatzky and Klein (1982) showed a consistent association between relative advantage and the adoption behavior. Also, comparing eight models explaining individual acceptance, Venkatesh et al. (2003) showed that relative advantage consistently and significantly affects technology adoptions over time. The more advantageous the innovation is perceived by potential adopters, the greater chance it will be adopted (Agarwal and Prasad 1997; Plouffe et al. 2001). We predict the relative advantage positively influence individual acceptance of big data over time.

Trialability. Trialability would have significant effects on individual acceptance of big data. The reason might be that data analytics are costly and running some trials can give potential adopters considerable insights into the functionality and results of the analytics, all of which are necessary for making adoption decisions (Barton and Court 2012).

Ease of use (i.e. the reversal of complexity). Ease of use is the degree to which an innovation is perceived easy to use (Venkatesh et al. 2003), and is the reverse of complexity in Rogers' work. Applying to big data adoption, the predictive power of complexity might be less straightforward. Analytics do not make the decision easier, but rather more difficult. Davenport et al. (2001) list the various skills and experience to turn data into knowledge. Building these capabilities is not as easy as applying intuition. Marketers, who pursue the real value from data, would not reject real analytics because of its high level of complexity, whereas marketers, who appreciate intuitions, would probably reject analytics because it is not easy to use. Thus, ease of use might not be a prerequisite of analytics adoption.

Information seeking (i.e. compatibility). Rogers' (1995) diffusion theory identifies at least three different kinds of compatibility, but two of them do not apply to this context. For example, there is compatibility with one's cultural values and beliefs, and with one's need for the innovation. We focus on compatibility with one's experience. For example, some managers may already seek out information regarding consumers and markets (Hirschman 1980). For them, analytics would be a compatible innovation. However, others do not have experience with being open to new information and for them, analytics may not be compatible with their past experience. A potential adopter preoccupied with the incompatibility of analytics would not be open to or seek out new analytics. That is, one's information seeking reflects his/her perceived compatibility of new ideas. Thus, it is reasonable to propose that information seeking (i.e. compatibility) also affects the analytics adoption behaviors.

Observability. The effect of observability on adoptions varies. Agarwal and Prasad's (1997) study showed that observability has significant impacts on the intention to adopt World Wide Web, whereas Venkatesh et al. (2003) studied four innovations in four sectors and found that the observability has no significant effects during the whole adoption process. Moreover, big data analytics contains ideas and various methods and tools (Barton and Court 2012). The nature of big data analytics leads to the varying observability of each element. Both of previous findings and the nature of big data analytics throw difficulties on proposing the effect of observability on the big data adoption behaviors.

Contextual factors and interactions

Although the value of the five innovation attributes may be well justified by some—but not all—researchers, a more critical issue is whether the strength of these effects depends on organizational contexts. Studies have shown contextual factors significantly affect individual acceptance of innovation. For instance, Karahanna et al. (1999) found that external pressure from the top management and supervisors could override the effects of individuals' initial inertia in adopting new technologies. Despite the harmony in the inclusion of contextual factors in individual acceptance of innovation research, inconsistencies are on the effect sizes and directions of some key contextual factors. For instance, some studies show that a more centralized organization is more ready for innovation implementation (e.g. Zaltman et al.

1973), whereas others hold the opposite (e.g. Damanpour 1991; Wierenga and Ophuis 1997). Moreover, conflicting theoretical formulations and empirical results have resulted in the ambiguous role of external pressure in the individual acceptance of innovation model. Some studies found mandates from supervisors increased individual adoption intentions and usage (e.g. Agarwal and Prasad 1997; Karahanna et al. 1999), whereas the findings of Venkatesh et al. (2003) did not support it.

It seems not appropriate to simply generalize the persuasive effects of contextual factors on individual acceptance of innovation. It is better to investigate when and how they are effective, rather than whether they are effective. In the meta-analysis research, Damanpour (1991) suggested that organization types and adoption stages should be distinguished as contingency variables of innovation adoptions. That is, the determinants of innovation vary with the change of the organization context and the adoption stage. We may derive two implications here. One is that the effects of contextual factors change across innovation stages. The other is that the predictive power of innovation attributes is contingent on both organizational contexts and innovation stages. To examine the dynamics of innovation attributes, contextual factors and individual acceptance of big data, we suggest two key contextual factors that need to be addressed: centralization and organizational politics.

Organizational Politics. Although politics players may not like the objective insights from big data, the influence of politics is not consistently harmful (Eisenhardt and Bourgeois 1988; Sasser and Koslow 2012). For example, Eisenhardt and Bourgeois (1988) suggested that politics harms performance, because politics distracts the top management team, evaporating their energy, restricting information flows and distorting the perceptions of other ideas. However, Sasser and Koslow (2012) found that when the organization is supportive and appreciate new ideas, a high-level of politics may lead to a high-level of individual creativity. This could be because the organization support offsets the negative impacts of politics by providing a firewall that protects innovators (Sasser and Koslow 2012). How politics interacts with big data attributes and affects individual acceptance of big data is worth of investigation.

Organizational politics appear in a myriad of different forms. According to the literature on politics (Eisenhardt and Bourgeois 1988; Gandz and Murray 1980), we define politics in this study as those behaviors that are intentional, often conducted in a devious and underhanded way, used to achieve self-interest which conflicts with some other individuals, and might, but not always, harm organizational effectiveness.

Eisenhardt and Bourgeois (1988) found five ways, in which politics is played out within organizations, namely withholding information, controlling agenda, co-optation of major decision makers, participating "outlaw" staff meetings and forming external alliances. These techniques are employed intentionally by individuals to inappropriately manipulate decision-making. Politics can be seen as an informal way to manipulate the decision and thus greatly affect the adoption of objective informative tools like big data analytics.

Eisenhardt and Bourgeois (1988) provided examples of how politics negatively impact the organizational decision-making process. For example, top management teams may play political games such as withholding information from subordinates and forming the internal alliance to manipulate the decision-making process inappropriately. Also, by hiring external consultants to justify the legitimacy of the decision that has already been made, managers can distort employees' perceptions of certain ideas. Applying to the analytics context, game playing can be highly disruptive because politics would impact individuals' perceptions of analytics and thus the adoption of data analytics. Political players tend to avoid using data because the insights from data are objective and might not always be in agreement with managements' personal agenda. When top managers are political and self-interest driven, the data-driven strategy might threaten their power to control organizational agenda.

Widespread political gamesmanship may weaken the effect of information seeking (i.e. compatibility) on individuals' intentions to adopt big data because managers in politicized organizations perceive little compatibility with the data analytics approach, which seeks the objective quantifiable truth. As Eisenhardt and Bourgeois (1988) report, game players usually have hidden agendas and manipulate the decisions to achieve their goals. Descriptive analytics such as visualization methods and tools are often abused by those with a political agenda because the information is more easily manipulated than insights from predictive models (Bhandari et al. 2014). The predictive models associated with big data are too "honest" and complex to survive politics. Thus, relatively speaking, those analysts, who regularly seek out new information, know that big data analytical tools may not be politically accepted and thus feel held back in introducing the tools. That is, the presence of politics inappropriately screens out those analytics which may oppose top managements' agenda. So we propose that politics weakens the strength of the relationship between information seeking and intention to adopt analytics during the pre-adoption period.

Hypothesis 2.1: The presence of organizational politics suppresses the positive effect of information seeking (i.e. compatibility) on individuals' intentions to adopt big data during the pre-adoption period.

Similarly, in highly political context, the trialability of big data has weaker effects on individual intentions to adopt big data. Trialing big data allows individuals to understand the application, the benefits and costs of big data. The more trials of big data, the more clearly individuals understand the incompatibility between big data and politics and the conflicts between data-driven individuals and game players. In political contexts, higher trialability of big data might not increase individuals' intentions to adopt big data. That is, the trialability of big data has weaker impacts on the intentions to adopt big data in political environments than in non-political ones. We predict that organizational politics weakens the positive relationship between trialability and the intention to adopt big data.

Hypothesis 2.2: The presence of organizational politics suppresses the positive effect of trialability on individuals' intentions to adopt big data during the pre-adoption period.

Despite the incompatibility between big data and politics, individuals may find there are many insights to gain from big data in order to survive political environments. That is, the value of big data is much higher in political environments than in non-political ones. Thus, to survive politics, individuals care about the benefits of big data when considering adoptions. It is reasonable to propose that organizational politics amplifies the strength of the relationship between relative advantage and the intention to adopt big data.

Hypothesis 2.3: The presence of organizational politics enlarges the positive effect of relative advantage on individuals' intentions to adopt big data during the pre-adoption period.

Centralization. Organizational centralization is a frequently studied contextual factor in innovation research, but the effects of centralization on adoption behaviors are not uniformly beneficial. Kimberly and Evanisko (1981) found that centralization facilitated administrative innovations but hinders technological ones. And the reason was that technological innovations, often applied by professionals at the departmental level for operational decisions, were less relevant to central decisions and thus more autonomy may result in more efficient adoption decisions. Consistent with this notion, studies on the use of market research also show that centralization has negative effects on marketing managers' willingness to utilize market research (Deshpande 1982; Deshpande and Zaltman 1982). Low levels of centralization mean higher freedom in performing the job and more responsibilities in making decisions. When managers bear more responsibility, they tend to obtain more information to reduce uncertainty and support the decisions they need to make (Deshpande 1982; Deshpande and Zaltman 1982). Thus, previous findings suggested that the effects of centralization depend on the roles of the innovations in central decision-makings.

Unlike the use of traditional market research approaches in Deshpande's study (1982), the adoption of big data analytics may be more beneficial to central decisions than departmental level ones. Big data analytics requires the creation of a data-driven culture, the building of a central big data platform with integrated data warehousing and analytical layers, and the recruiting of data scientists (Brown et al. 2011; McAfee and Brynjolfsson 2012). These costs may be significant, and decentralized departments may find the costs insurmountable. But in a centralized environment, these costs would be divided over several departments, and the philosophy of a uniform big data platform may be more achievable. Thus, relative advantage may differ in respects to centralization.

According to Kimberly and Evanisko (1981), centralization facilitates the adoption of innovations that are critical to central decisions. Thus, one may still see relatively high intentions to adopt big data in centralized organizations even if the perceived relative advantage of analytics is modest. On the contrary, in a decentralized organization, lower level of relative advantage might result in fewer intentions to adopt big data, because the top management teams of decentralized organizations have little motivations to spend the time, effort and money to adopt enterprise-wide big data analytics. It may still be that the more benefits are perceived in a decentralization context, the higher intention to adopt data analytics. Such may be the same for centralized organizations, such that if relative advantage is large enough, the management will develop the necessary organization-wide system to make analytics happen. Thus, relative advantage should be more important in decentralized organizations.

Hypothesis 2.4: Organizational centralization weakens the relationship between relative advantage and individual intentions to adopt big data.

Given that big data analytics requires an enterprise-wide platform (Brown et al. 2011; McAfee and Brynjolfsson 2012), decentralization may buffer the strength of the relationship between information seeking (i.e. compatibility) and big data analytics adoption. Analysts in decentralized organizations, who routinely seek out new information, probably have little experience with big data analytics, because the decentralized decisions they focus on do not require the support of an integrated data platform and analytics function. These analysts may still value analytics due to high-perceived relative advantage, but not due to compatibility with their prior seeking of information.

In a centralized context, however, the positive effect of information seeking on adoptions is amplified. These analysts, open to new solutions and insights, might have more experience with the kind of enterprise-wide platforms compatible with adopting big data analytics.

Managers of centralized organizations just have more exposure to organization-wide thinking that will make big data compatible with how they seek out information. And so the positive effect of information seeking (i.e. compatibility) on analytics adoptions is strengthened in a centralized context. Therefore, we propose that:

Hypothesis 2.5: Organizational centralization enlarges the positive effect of information seeking (i.e. compatibility) on individuals' intentions to adopt big data during the pre-adoption period.

Similarly, centralization may increase the positive relationship between trialability and the intention to adopt big data. As stated before, the trial of big data allows individuals gain insights into the application, advantages and disadvantages, and the potential outcomes of big data. With more opportunities to try out big data, individuals can more clearly see the compatibility between big data and centralized structure, leading to higher intentions to adopt big data.

Hypothesis 2.6: Organizational centralization strengthens the positive influence of trialability on individuals' actual usage of big data during the post-adoption period.

Once the big data is adopted by the organization and available to individuals, contextual factors may have little influence on current big data users. Big data users are those whose organizations have adopted big data. In other words, big data users are those have access to big data. Moreover, current users are those who have gone through the behavioral modifications process from adoption to actual usage (Agarwal and Prasad 1997). While external pressure has influences on the initial acceptance of the innovation, it may have few influences on current usage (Agarwal and Prasad 1997; Karahanna et al. 1999). The reason that subsequent usage involves much more magnitudes of behavioral modifications than initial adoption stage. Contextual factors may facilitate or inhibit adoption intentions during the pre-adoption stage. Once the behavioral modification process is passed, users would base the decisions on the individual assessment of the big data (Agarwal and Prasad 1997). That it, the actual usage of big data is dependent on individual perceived attributes of big data, and contextual factors have few effects on users after the adoption.

Methods

In-depth interviews were conducted with 21 data users from 18 organizations to pre-test our hypotheses. Eight respondents were from data analytics consulting firms, whereas the other 13 were from banking and financial service industry, telecommunication industry, fast moving consumer goods industry and other data-intensive fields. Moreover, questionnaires were collected from 337 respondents from marketing analytics websites. Respondents self-assessed their perceptions of big data attributes, adoption intention, use intention and actual usage of big data. All 337 respondents reported on the pre-adoption period, but a subset of 149 respondents actually adopted and for them it was possible to estimate post-adoption intention to use as well as actual use.

Survey data description

As it is not only marketing employees, but also people from a wide range of departments and all hierarchical levels that are extracting customer insights from data to support decisions, our target respondents were practitioners using or considering using big data to understand customers. They could be either big data users or potential adopters. An online survey with separate questions for big data users and potential adopters was developed. The survey link was posted on seven marketing-related groups from two data analytics professionals' networking websites with the permission of groups' organizers. These data analytics websites were open to all who were interested in data analytics, and the chosen seven groups focused on data analytics for marketing professionals.

Given the limited availability of website statistics, we estimated the respondent rates from two websites separately. On one data analytics website, we found three marketing-related groups and the estimated homepage traffic per day for three groups was 15 according to their web statistics. The survey link stayed on the three groups' homepages for

16, 21 and 21 days respectively. The estimated number of survey link browsers of the three groups' webpages was 870. For the other data analytics networking website, we found four marketing-related groups. The site emailed to group members when any information was posted on the webpage so the sampling frame in these four groups were all the groups' members, which were 888 individuals (202, 350, 220 and 116 unique members respectively). Completed surveys numbered 337, for a response rate of 19%.

Sample characteristics

Table 2.1 ***Questionnaire Samples Demographics (Study 1)***

Demographic variables	Pre-adoption		Post-adoption	
	Frequency	**Percentage**	**Frequency**	**Percentage**
Gender				
Male	192	57.0	88	59.1
Female	145	43.0	61	40.9
Age				
18-25	12	3.5	6	4.0
26-35	86	25.5	55	36.9
36-45	83	24.6	34	22.8
46-55	85	25.2	38	25.5
56-65	56	16.6	10	6.7
65+	15	4.5	6	4.1
Hierarchy rank				
C-suite (CEO/CMO)	54	16.0	13	8.7
Executive-level management	30	8.9	14	9.4
High-level management (*e.g.* department manager)	64	19.0	48	32.2
Mid-level management *(e.g.* coordinator)	59	17.5	34	22.8
Lower-level management (*e.g.* executives)	30	8.9	4	2.7
Senior employees	73	21.7	26	17.5
Entry-level employees	27	8.0	10	6.7
Years in the firm				
0-5 years	104	30.9	54	36.2
6-10 years	117	34.7	62	41.6
11-15 years	46	13.6	15	10.1
16-20 years	35	10.4	11	7.4
21-25 years	8	2.4	3	2.0
26-30 years	17	5.0	4	2.7
30+	10	3.0	0	0
Years in the industry				
0-5 years	59	17.5	20	13.4
6-10 years	85	25.2	62	41.6
11-15 years	46	13.6	21	14.1
16-20 years	59	17.5	23	15.4
21-25 years	29	8.6	12	8.1
26-30 years	21	6.2	7	4.7
30+	38	11.3	4	2.7
Number of responses	$N_{pre\text{-}adoption}$=337		$N_{post\text{-}adoption}$=149	

The sample characteristics are shown in Table 2.1. Respondents who had not started to use big data to understand customers answered questions for the pre-adoption period, and big data users answered questions both of the pre- and post-adoption periods. The female ratio of the respondents of the pre-adoption period was 43.0 percent, and that of the post-adoption period was 40.9 percent. Both female ratios were close to the world female ratio of 2015 calculated by World Bank[2]. The respondents during the pre-adoption period were a combination of specialists and managers from different levels, with over 70 percent from management roles (84 top managements, 64 high-level managements and 89 mid- and low-level managements). Similarly, of the respondents during the post-adoption period, over 70 percent were from management positions. As using data analytics to understand customers was not just for particular roles or departments, but important to any decision-making process, the sample with respondents from bottom-to-top hierarchical levels provided comprehensive insights to our research.

Measures

Items for relative advantage, ease of use (*i.e.,* the reversal of complexity), trialability and observability were adapted from literature (Agarwal and Prasad 1997; Moore and Benbasat 1991); items for centralization were adapted from Deshpande (1982); items for information seeking (*i.e.,* compatibility) and strategic responsiveness were developed based on the words and phrases used by interviewees; and items of politics were developed based on interview findings, as well as Eisenhardt and Bourgeois' (1988) qualitative study of politics in organizational decision-making process. Lists of the items can be found in Table 2.2.

Items for intention to adopt and use of big data during both the pre- and post-adoption periods, and the actual usage of big data (Table 2.4) were adapted from prior studies in individual acceptance of technology (Davis et al. 1992; Venkatesh et al. 2012). All items were measured on a seven-point Likert scale with a rating of "-3" indicating "strongly disagree" to a rating of "+3" indicating "strongly agree".

[2] http://data.worldbank.org/indicator/SP.POP.TOTL.FE.ZS

Results

We performed Partial Least Squares (PLS) path modeling to test our framework. The main benefits were that it is suitable to analyze multiple relationships among blocks of variables and relaxes the multivariate normality needed for maximum likelihood–based SEM (Sanchez 2013, Hair et al. 2012). Another benefit of PLS path modeling is its high statistical power in establishing structural models even with a small sample size (Sarkar et al. 2001; Hair et al. 2012). We conducted the PLS path analysis with the package "plspm" in R.

Measurement model. We followed the study of Hair et al. (2012) to assess the quality of measurement model through examining indicator reliability, internal consistency reliability, convergent validity and discriminant validity.

With high factor loadings (average loadings = .885) and Cronbach's alphas (average Cronbach's alpha = .921), the indicator reliability and internal consistency reliability of measurements appeared strong (Table 2.2 and 2.4). All items loaded on expected variables as expected except items for observability. The reasons might be the complexity of big data analytics and the varying observability of different elements of analytics as mentioned in the theory development section, and we dropped the observability construct.

For those who adopted analytics, their pre-adoption responses would be retrospective compared to those who were still in the pre-adoption period for their firms. We introduced a dummy variable to indicate the absence and presence of retrospective data. Results showed that this variable has no significant effect in the models (p = .9191).

All dependent variables had Average Variance Extracted (AVE) above 65% (Table 2.4). A rule of thumb is to check AVE of 50% or more (Sarkar et al. 2001). Our measurement model, thus, showed an acceptable level of convergent validity.

We also calculated the cross-loadings to assess the discriminant validity (Table 2.2 and 2.4). All items had higher loadings on expected constructs than others (Table 2.2), indicating that there was no traitor item and providing reasonable evidence of discriminant validity.

Table 2.2 *Cronbach's Alpha and Cross-loadings for Independent Variables (Study 1)*

Items	Centralization	Politics	Information seeking	Relative advantage	Ease of use	Trialability
If I wish to make my own decisions, I would be quickly discouraged.	**0.9640**	0.5254	-0.3240	-0.0086	0.1139	0.0932
Even small matters of my job have to be referred to someone higher up for final answers.	**0.8000**	0.5792	-0.3012	-0.0928	0.0836	0.0641
I have to ask my boss before I do almost anything.	**0.7150**	0.5413	-0.2937	-0.0618	0.0606	0.0269
Any decision I make has to have my boss' approval.	**0.7468**	0.6098	-0.2847	-0.0689	0.0760	0.0479
In our department, senior management sometimes distorts information.	0.5686	**0.8169**	-0.2366	-0.0130	-0.0101	-0.0664
Some top management pursues their own self-interests and squash other people's ideas.	0.5659	**0.8976**	-0.0604	0.0874	0.0394	0.0233
The senior managers ally with their proponents to push their views.	0.4790	**0.8917**	-0.0302	0.0889	-0.0226	0.0167
Some managers co-opt those with the potential to hinder their goals.	0.5518	**0.8628**	-0.2004	0.0686	0.1035	-0.0439
If the result from external consultants does not meet managers' expectation, it will not be used.	0.3985	**0.7065**	-0.1196	0.0139	0.0226	-0.0241
I regularly explore information about markets.	-0.3500	-0.1841	**0.7995**	0.1994	0.1340	0.1861
I often seek out information about new customer behavior trends.	-0.2483	-0.1055	**0.8588**	0.2023	0.1355	0.1634
I frequently search for information about new ways to understand customers and markets.	-0.2927	-0.0860	**0.8968**	0.1782	0.1074	0.2191
I actively look for information about new methods to understand consumers.	-0.2953	-0.0476	**0.8938**	0.2284	0.1467	0.2024
Big data analytics gives me great insights into market & customer changes.	-0.0836	0.0169	0.2309	**0.8872**	0.5063	0.2940
Big data analytics enables me to gain insights into consumers more quickly.	-0.0301	0.1082	0.2213	**0.8603**	0.4395	0.2945
Big data analytics improved/improves the quality of my understanding of markets and customers.	-0.0327	0.0546	0.1763	**0.8952**	0.5237	0.2714
Big data analytics makes it easier to understand consumers.	0.0213	0.0761	0.1953	**0.8845**	0.5114	0.3210
I believe that it is easy to use big data to do what I want it to do.	0.0304	-0.0011	0.1720	0.4804	**0.9125**	0.4743
Learning to operate big data system is easy for me.	0.0956	-0.0197	0.1281	0.4972	**0.9179**	0.5071
How I would interact with big data is clear and understandable.	0.1260	0.0426	0.1386	0.5584	**0.9482**	0.4942
Overall, I believe that big data is easy to use.	0.1661	0.0815	0.1251	0.5333	**0.9246**	0.4899
I am permitted to use big data on a trial basis long enough to see what it could do.	-0.0009	-0.0233	0.2435	0.3190	0.5098	**0.8977**
Before deciding whether to use big data, I have many opportunities to try various big data approaches.	0.0990	-0.0214	0.1628	0.3042	0.4472	**0.9239**
Before deciding whether or not to use big data, I am able to properly try out big data solutions.	0.0924	0.0073	0.2300	0.3613	0.4862	**0.9317**
Big data solutions are available to me such that I could adequately test run various applications.	0.0719	-0.0189	0.2186	0.2629	0.4682	**0.9296**
I know where I can go to satisfactorily try out various uses of big data.	0.1652	0.0164	0.1599	0.2700	0.4977	**0.8645**
Cronbach's alpha	**0.904**	**0.895**	**0.885**	**0.905**	**0.945**	**0.948**

Table 2.3 *Cronbach's Alpha and Factor Loadings for Dependent Variables (Study 1)*

Items	Adoption intention	Actual Usage
I intended to use big data.	0.8942	
I predicted that I would use big data in the future.	0.9081	
If I had the power to decide whether to use big data, I would say yes.	0.8386	
I was hoping to apply big data for my work.	0.9218	
At present, I consider myself to be a frequent user of big data.		0.8505
At present, I use big data for my work regularly.		0.8954
I currently use big data routinely for my work.		0.9157
Big data has now become a regular part of my work.		0.9281
Cronbach's alpha	**0.913**	**0.920**
Sample size	**337**	**149**

Table 2.4 ***Average Variance Extracted and Correlation Matrix (Study 1)***

	Constructs	1	2	3	4	5	6	7	8
1	Centralization	**0.66**							
2	Politics	0.69	**0.70**						
3	Information seeking	-0.44	-0.19	**0.75**					
4	Relative advantage	-0.19	-0.10	0.37	**0.78**				
5	Ease of use	-0.12	-0.03	0.27	0.81	**0.86**			
6	Trialability	-0.16	-0.08	0.33	0.78	0.79	**0.83**		
7	Intention to adopt	-0.01	0.12	0.34	0.19	0.14	0.13	**0.79**	
8	Usage	-0.12	-0.05	0.47	0.58	0.56	0.65	0.14	**0.81**

Note: The diagonal (in bold type) shows the average variance extracted of the indicators.

Predicting intention to adopt big data during the pre-adoption period. Intention to adopt big data had 65.2 percent of variance explained (Table 2.5). Results showed that relative advantage ($\beta = .575, p = .0000$), trialability ($\beta = .389, p = .0000$), information seeking ($\beta = .263, p < .05$), and centralization ($\beta = .213, p < .05$) had direct effect on intention to adopt big data during the pre-adoption period. Results also showed six significant interactions (between politics and relative advantage ($\beta = .822, p < .001$), centralization and relative advantage ($\beta = -1.016, p = .0000$), politics and information seeking ($\beta = -.518, p < .01$), centralization and information seeking ($\beta = .357, p < .05$), politics and trialability ($\beta = -.542, p < .01$), and centralization and trialability ($\beta = .585, p < .01$).

The six interactions are illustrated in Figure 2.2a, b, c, d, e and f, respectively. To construct the figures, high-level of politics was defined as one standard deviation above the mean, and low-level of politics was defined as one standard deviation below the mean. Similarly, high-level of relative advantage, information seeking, and centralization were defined as one standard deviation above their means, and low-level of them were defined as one standard deviation below their means. The levels in the graphs are predicted values for intention to adopt big data for one standard deviation below or above the means for politics, relative advantage, information seeking, and centralization.

Table 2.5 ***PLS Path Modeling Results: Big Data Attributes, Organizational Contexts and Individual Acceptance***

Exogenous variable	Individual acceptance of big data	
	Adopt Intention	Actual Usage
Intercepts	0.000	0.000
Organizational adoption [a]	-0.087*	
Big data attributes		
Relative advantage	0.575***	-0.036
Ease of use	-0.058	1.307***
Trialability	0.389***	0.015
Information seeking	0.263*	1.735***
Contextual factors		
Politics	0.232	0.175
Centralization	0.213*	-0.160
Interactions		
Politics × Information seeking	-0.518** *(H2.1)*	
Politics × Trialability	-0.542** *(H2.2)*	
Politics × Relative advantage	0.822*** *(H2.3)*	
Centralization × Relative advantage	-1.016*** *(H2.4)*	
Centralization × Information seeking	0.357* *(H2.5)*	
Centralization × Trialability	0.585** *(H2.6)*	
Information seeking × Ease of use		-1.789***
R^2	0.652	0.317
Sample size	337	149

* p < .05
** p < .01
*** p < .001
a. Organizational adoption is a binary variable, with 0 indicating that the respondents' organizations have not adopted big data, and 1 indicating those have adopted big data.

The slopes were compared to determine the difference of relationships (Aiken and West 1991). A steeper slope in one organizational context means a stronger impact for that context. Hypothesis 2.1 suggested that the presence of politics weakens the effect of information seeking on the intention to adopt big data. Figure 2.1a shows the effects when politics is high or low. The slope of the high politics line is -0.267 and that of the low politics line is 0.781 (Figure 2.1a). The difference in the slopes between the high- and low-politics contexts shows that when there is high politics, the effect of information seeking becomes negative. The reason is that individuals who are actively seeking new insights understand the incompatibility between big data and the politicized context better than those less active ones. Hypothesis 2.1 is supported.

Figure 2.1a Politics affecting the relation between information seeking and the intention to adopt big data

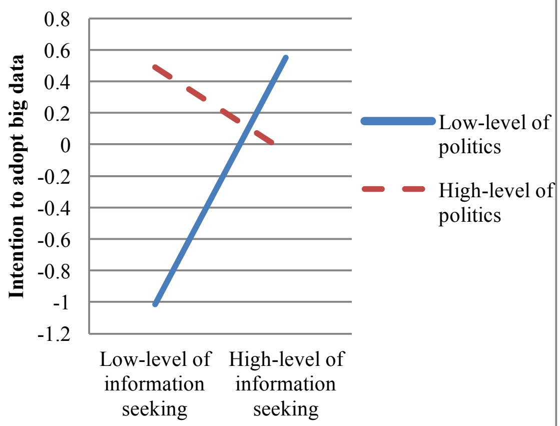


Figure 2.1b Politics affecting the relation between trialability and the intention to adopt big data

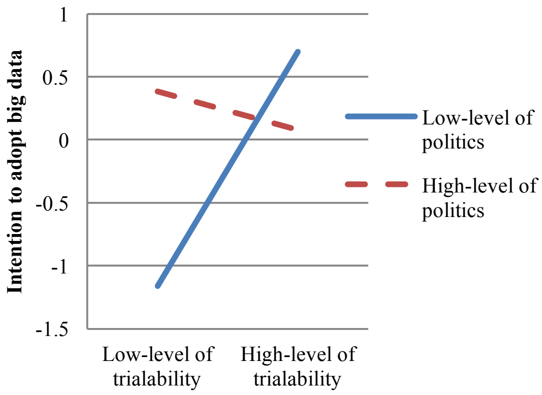


Figure 2.1c Politics affecting the relation between relative advantage and the intention to adopt big data

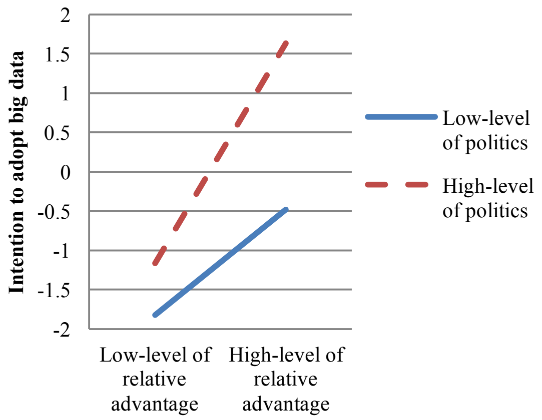


Figure 2.1d Centralization affecting the relation between relative advantage and the intention to adopt big data

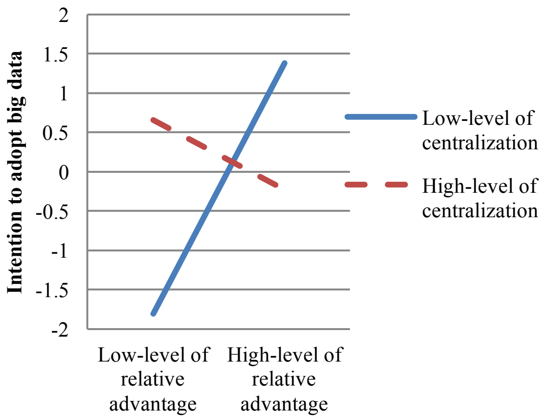


Figure 2.1e Centralization affecting the relation between information seeking and the intention to adopt big data

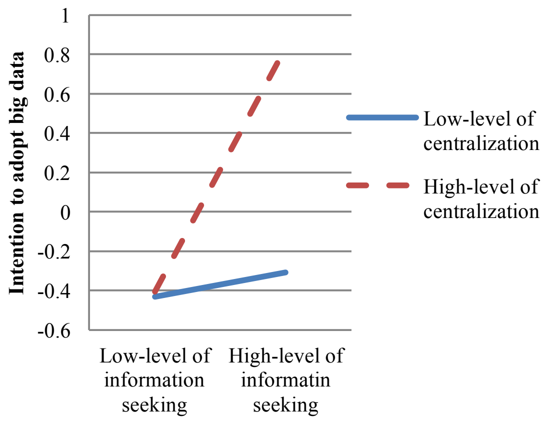
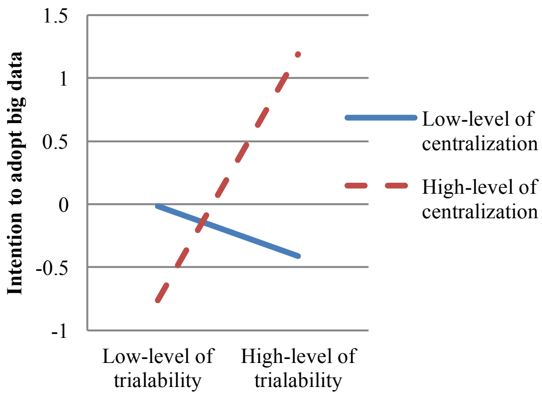


Figure 2.1f Centralization affecting the relation between trialability and the intention to adopt big data



Hypothesis 2.2 predicted that politics weakens the influence of trialability on individuals' intentions to adopt big data. Figure 2.1b shows the relationships between trialability and individuals' intentions to adopt big data when organizational politics is high or low. The slope of the low politics line is 0.930 and that of the high politics line is -.154 (Figure 2.1b). The contrasting slopes for the high- and low-politics contexts indicate that trialability is not a salient predictor of individuals' intentions to adopt big data in highly political contexts. Hypothesis 2.2 is supported.

Hypothesis 2.3 suggested politics enlarges the effect of relative advantage on the intention to adopt big data. Figure 2.1c shows the effect of relative advantage on the intention to adopt big data during the pre-adoption period when politics is high or low. The slope of the high politics line is 1.397 and that of the low politics line is 0.672 (Figure 2.1c). The difference in the slopes between the high- and low-politics contexts shows that relative advantage has a significantly larger effect on the intention to adopt big data in a highly political context than a less-political one. Hypothesis 2.3 is supported. In highly politicized contexts, individuals are more willing to use big data when they perceive high-level of relative advantage. The insights from big data prevent politicians from inappropriately manipulating decisions and hurting others' interests.

Hypothesis 2.4 suggested that centralization weakens the effect of relative advantage on individuals' intentions to adopt big data. As seen in Figure 2.1d, the slope for a centralized organization (-0.441) is flatter than that for a decentralized organization (1.591). Low-level of relative advantage yields significantly higher intention to adopt analytics in centralized organizations than in that in decentralized ones. However, the increase of the perceived relative advantage from big data does not lead to the increase of individuals' intentions to adopt big data in centralized context. That is, when centralization is high, relative advantage has a weaker effect on the intention to adopt big data. The absence of relative advantage as a predictor in centralized organizations may be due to the compatibility between centralization and enterprise-wide big data platform as the major benefit. The enterprise-wide big data platform fits centralized decision process well, and hence it is not surprising to see the weaker effect of big data's relative advantage in understanding customers on individuals' intentions to adopt big data in centralized organizations.

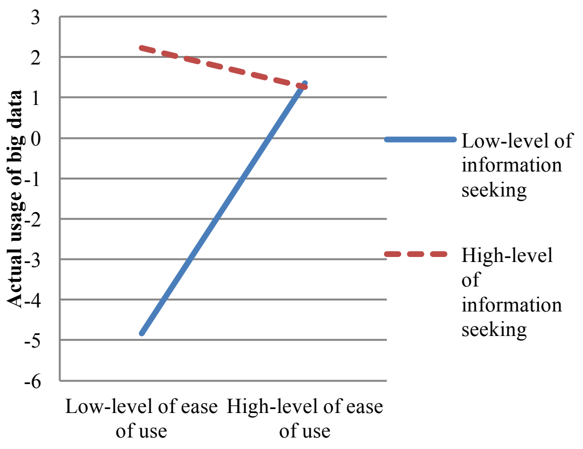
Hypothesis 2.5 suggested that organizational centralization increases the effect of information seeking on the intention to adopt big data during the pre-adoption period. Figure 2.1e shows the effect of information seeking on the intention to adopt big data during the pre-adoption period when organizational centralization is high or low. The slope of the high centralization line is 0.620 and that of the low centralization line is 0.061 (Figure 2.1e). The difference in the slopes between the high- and low-centralized contexts shows that when an organization is centralized, the effect of information seeking is significantly stronger. Thus, Hypothesis 2.5 is supported. This interaction is best explained by the compatibility between the centralized structure and big data platform.

Hypothesis 2.6 predicted that the trialability of big data has stronger effects on individuals' intentions to adopt big data in centralized contexts. Figure 2.2f illustrates the interaction between trialability and organizational centralization. The slope of the high centralization line is 0.974 and that of the low centralization line is -0.197. The difference between the two slopes supported Hypothesis 2.6 that trialability is a salient predictor in centralized organizations, not in the decentralized ones.

Predicting self-report actual usage of big data. Actual usage of big data had 31.7 per cent of variance explained. Information seeking ($\beta = 1.735, p < .0001$) and ease of use ($\beta = 1.307, p < .001$) had significant one-way effects on the actual usage of big data during the post-adoption period. The effects of contextual factors were not significant during the post-adoption period. It can be explained by the difference between initial adoption and subsequent use. Subsequent use requires much fewer changes of behavioral modifications than initial adoption. While individuals may want to conduct a full assessment of the environment and the innovation itself during the pre-adoption period, the decision for continuous use may be based on the innovation itself.

Results also showed the significant interaction between ease of use and information seeking ($\beta = -1.789, p < .001$). Figure 2.2 illustrates how the interaction between information seeking and ease of use affects the actual usage of big data. When individuals are actively seeking information to understand customers, they will use big data regardless of its complexity. But when individuals are not active information seekers, their big data usage is dependent on the complexity of big data. In other words, during the post-adoption period, individuals use big data only when either ease of use or information seeking is high.

Figure 2.2 The interaction between ease of use and information seeking affecting the actual usage of big data



Discussion

Before concluding, there are several possible limitations. The use of self-assessment may not have been ideal. The methodological format, which was retrospective, may have influenced results. The data collection via online communities may have excluded the views from those not involved in online networks.

However, this research bridged the gap by showing individuals' intentions to use big data during both the pre-adoption and post-adoption periods. The results illustrate the social life of organizations where contextual factors significantly affect individuals' perceptions and behaviors. This is a compelling extension of both the existing theories and methods.

Instead of generalizing whether contextual factors are effective, we showed when and how the contextual factors are effective. Regarding “when”, we found that contextual factors had significant effects during the pre-adoption period, rather than the post-adoption period. Compared to subsequent usage, that initial acceptance of big data requires larger extent of behavioral modifications, before which individuals tend to conduct a full assessment of the environment and the innovation itself to understand the potential benefits and risks. Once the individuals pass the behavioral modification process and move to the continuous use stage, their focus becomes the costs related to the continuous usage (i.e. the complexity and compatibility of big data).

Regarding “how” the contextual factors affect individual acceptance of big data, the relationships depend on big data attributes. We chose the centralization and the organizational politics as the contextual factors in our research. Big data is more suitable for centralized organizations, but less preferred by game players who intent to inappropriately manipulate decision process. Our findings showed the contrasting effects between centralization and politics. For example, centralization enhanced the positive effect of information seeking (*i.e.* compatibility), whereas politics weakened it. The reason is that resource intensive big data approach is more suitable for centralized organizations to coordinate data structure across the organization, but the active use of objective data and information is conflicting with the highly-politicized context. The same reason might explain the contrasting effects of centralization and politics on the relationship between trialability and the intention to adopt big data. Furthermore, the effects of centralization were dependent on the big data attributes. For example, centralization has more significant positive effects when information seeking or trialability is high. That is, when individuals are highly data-driven and have opportunities to try big data, the positive effect of centralization on adoption intentions is stronger. The results demonstrate that it is not appropriate to simply generalize whether the organizational context is effective or not, the proper way to investigate when and how it facilitates or inhibits individual acceptance of big data.

There was another noteworthy result. It is widely assumed that ease of use should yield a positive effect on innovation adoption. However, we found no significant effect from ease of use during the pre-adoption period. This might be because that some analytics, such as predictive modeling, creating more value but not making markers' jobs easier, whereas some other analytics, such as basic data visualization and reporting system, are more intuitive and user-friendly in comparison. Future research may consider examining the predictive power of ease of use of different types of analytics separately.

It has been overlooked that conflicts between organizations' and decision makers' interests might lead to the inappropriately rejection big data. Effective big data analytics helps the organizations to understand customers better, but does not necessarily help decision makers to get promoted, earn more pays, or survive the political game of organizations. In other words, although big data brings value to the business, it might not meet decision makers' individual expectations and self-interests, resulting in the inappropriate rejection.

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CHAPTER 3: WHEN DO CONSULTING FIRMS FACILITATE THE BIG DATA INNOVATION PROCESS? A SOCIAL CAPITAL PERSPECTIVE

Abstract

Increasingly more organizations form strategic partnerships with consulting firms such as IBM and McKinsey to seize the potential of big data (Manyika et al. 2011; Pressman 2015). But few studies have shown how consulting firms affect big data adoption process. This study investigated the effects of consulting assets, the social capital from consulting networks, on three sequential steps of the big data innovation process (i.e. adoption, diffusion and implementation), in an attempt to pinpoint when social capital matters. Our hypotheses were tested based on a sample of 337 marketers, 188 of whom were big data innovation prospects and 149 were big data users. The study showed that the effects of consulting ties were not significant on the adoption stage, but significant on both of the diffusion and implementing stages, suggesting a facilitating role rather than a motivating role of consulting firms in big data innovation process.

Introduction

Big data has been recognized as an important source of competitive advantage (Manyika, Chui, Brown, Bughin, Dobbs, Roxburgh and Byers 2011). Researchers show that big data-driven decision contributes to 5 to 6 percent increase in profitability (Barton and Court 2012; Brown, Chui and Manyika 2011; McAfee and Brynjolfsson 2012). Moreover, according to McKinsey Global Institute, big data has a potential value equal to 300 billion dollars annually to US health sector, potential customer surplus equal to 600 billion dollars globally and has potential in increasing retails margin by 60 percent (Manyika et al. 2011). Empirically, companies like Google, Amazon and IBM have been able to extract value from big data and achieved new competitive differentiation (Barton and Court 2012).

Instead of implementing big data analytics alone, some organizations prefer allying with big data consulting firms. According to Yahoo Finance, more and more retailers hire IBM to analyze and secure customer data to improve marketing performance (Pressman 2015). Facebook also partners up with IBM in an attempt to extract more insights from its enormous customer data (Bort 2015). The prevalence of partnerships with consulting firms has raised a question. That is, how do consulting firms affect big data innovation process? However, no real theory has emerged to show the roles of consulting firms in the innovation process. Resource-based views suggest the social capital perspective to address this issue (Nahapiet and Ghoshal 1998).

However, existing studies offer rather inconclusive views on how social capital affects innovation process. Some added social capital into their frameworks (e.g. Taylor and Todd 1995; Venkatesh and Davis 2000), whereas some others did not (e.g. Agarwal and Prasad 1997; Davis 1989). Some found the correlation between social capital and innovation adoption depended on organizational settings, whereas some others found social influence has effects contingent on demographics factors. For example, Venkatesh and Davis (2000) found that the effects of social influences were significant in mandatory contexts, whereas

Venkatesh et al. (2003) showed that social influence did not have significant one-way effects on individual acceptance and usage generally, but it was more effective to elder people, particularly women. In contrast, Landry, Amara and Lamari (2002) found that consulting ties do not affect the likelihood to innovate. The inconsistent findings, together with the prevalence of consulting partnerships, call for further investigations into how social capital from consulting firms affects big data innovation process.

Against this backdrop, this study examines the effects of consulting firms on three sequential big data innovation steps in the marketing context. The first step in big data innovation process is adoption. Venkatesh et al. (2003) have demonstrated that social influence does not have a direct impact on users' intention to adopt technology. The reason might be the undetermined value anticipation and motivations of the potential adopters during the pre-adoption period. Without value anticipation and motivations, social capital would not lead to resource and capability exchanges (Nahapiet and Ghoshal 1998). Thus, it is tempting to predict that consulting firms do not affect individuals' intentions to adopt big data.

The second step is diffusion, at which organizations have adopted big data and are diffusing the use of big data across departments. As mentioned, motivations and value anticipation are two preconditions for social capital to work (Nahapiet and Ghoshal 1998). At the diffusion stage, the adoption decision at the organizational level is a strong external motivation for individuals to use big data. The effects of consulting firms, therefore, depend on individuals' anticipation of big data. For example, consulting firms can encourage individuals to use big data when they perceive high value from big data. However, when individuals perceive little value from big data, the effects of consulting firms might be negative. Following the value expectancy view, we predict that it is the effects of consulting firms depend on individuals' expectation of big data.

The third step is implementation, at which marketers routinely use big data for work. At this stage when marketers' motivations and value anticipation are determined, marketers' big data usage is mainly affected by their capabilities. As mentioned, big data implementation requires a broad range of technical skill and technology inputs. The inputs include new technology infrastructure (e.g. storage, computing and processing), new tools (e.g. analytical tools), new skill sets (e.g. IT, data science, and decision science) and other resource and capability inputs that can hardly be done by a single organization (Chen, Chiang and Storey 2012; Manyika et al. 2011; McAfee and Brynjolfsson 2012). Access to consulting firms enables the exchanges of know-how and know-what knowledge, improving marketers' capability in using big data (Nahapiet and Ghoshal 1998). Consistently, Deshpande and Zaltman (1982) also found that interactions between researchers and marketers have direct effects on the use of market research. In our study, it is reasonable to predict that consulting ties, which enable the exchanges of know-how and know-what knowledge, directly assist big data usage during the implementation stage.

In the following sections, we first develop hypotheses based on the literature review on innovation and social capital, and the emphasis is on the roles of consulting firms in big data innovation process (i.e. adoption, diffusion and implementation), and interactions between consulting assets and big data attributes. Second, methods and sample are discussed. Datasets from 337 marketing professionals are used to build models for intention to adopt big data at the adoption stage, intention to use big data at the diffusion stage and the actual usage of big data at the implementation stage. Finally, results, implications, limitations and further research are discussed.

Theory Development

In our research, we capture the big data innovation process with three stages, including adoption, diffusion and implementation. In the innovation assimilation theory, adoption and implementation are two major steps (Frambach and Schillewaert 2002; Fichman and Kemerer 1997; Tornatzky and Klein 1982). To capture the stage when big data is approved and adopted by organizations but not fully implemented, we add a diffusion stage between adoption and implementation. Capturing the diffusion stage, we would be able to examine how consulting firms influence the spread of the big data within an organization.

In the big data innovation context, consulting firms can be considered as a type of social capital. Social capital was introduced from sociology to explain innovations in late twentieth century. Beginning with Nahapiet and Ghoshal's (1998) work, a few researchers have demonstrated that social capital facilitates innovation adoption (Carmona-Lavado et al. 2010; Hsieh and Tsai 2007; Landry et al. 2002; Moran 2005). While previous studies have investigated the effects of social capital on innovation adoption, studies have shown that social capital might not always be effective and beneficial (Gulati and Higgins 2003; Landry et al. 2002; Wulf et al. 2001; Xiong and Bharadwaj 2011). The inconsistent findings might be resulted from the neglect of the four preconditions for social capital suggested by Nahapiet and Ghoshal (1998). In this section, we will discuss the changing conditions in big data innovation process, and how the effects of consulting firms evolve accordingly. Specifically, the potential effects of consulting firms on each step of big data innovation will be reviewed, based on which theoretical framework are built. We proposed that consulting assets, the social capital embedded within consulting ties, are the diffuser and facilitator rather than the motivator of big data innovation.

Consulting assets: the social capital from consulting firms

Social capital, which is an important resource of social actions (Coleman 1988), has been introduced to innovation studies (Nahapiet and Ghoshal 1998). Researchers have defined social capital in different ways. Bourdieu (Portes 1998, pp 3) first defined social capital as "the accumulation of the actual or potential resources which are linked to possession of a durable network of more or less institutionalized relationships of mutual acquaintance or recognition". Adler and Kwon's (2002) summary of social capital definitions from the perspectives of external relations, internal relations and both types of linkages offers an overview of the development of social capital. The prevailing suggestion is that social capital contains two elements, the social network and the relevant assets that are obtained through interactions among actors in the network (Bourdieu 1980; Burt 2009; Nahapiet and Ghoshal

1998; Portes 1998). For example, Nahapiet and Ghoshal (1998, pp.243) defined social capital as “the sum of the actual and potential resources embedded within, available through, and derived from the network of relationships possessed by an individual or social unit”. Also, Portes (1998) argued in favor of Bourdieu’s analysis, which treats social capital as an instrument and agreed that individuals can benefit from participating in groups and deliberately constructing of sociability both of which enable actors to obtain resources. Others explain social capital slightly differently. Coleman (1988) emphasized the function. He suggested that social capital is made up of networks and enables interactions within the networks. Baker (1990) stated that networks can be exploited to pursue particular interests. In this research, we defined consulting assets as the social capital derived from individuals’ relationships with external consulting firms. Consulting ties enable the interactions with external consultants and allow the exchange of know-what and know-how knowledge.

Social capital mainly has two dimensions: the structural and the relational (Landry et al. 2002; Nahapiet and Ghoshal 1998). The first dimension is structural, which is referred to the arrangements and connections among actors (Burt 2009; Nahapiet and Ghoshal 1998). The network tie is one important facet among others, by which actors are linked to one another (Wasserman and Faust 1994; Nahapiet and Ghoshal 1998). The nature of the linkage can be various, such as transactional or non-transactional, friendship or blood relationship and so forth (Wasserman and Faust 1994). For example, Baker (1990) classified the market relations into three categories, relationship interface, transaction interface and hybrid interface. Various networks types form different types of social capital. The reason is that linkages constitute interacting channels, and different types of ties might generate different capital flows. For example, some relationships are long enduring but not transactional, yielding restricted information flow rather than monetary flows (Baker 1990). Following Bake’s classification (1990), consulting relationships are transaction-based, and the information flows in the consulting networks are restricted by the value expectation and motivations of those actors, who have more bargaining power (Burt 2009; Seibert, Kraimer and Liden 2001).

Relationship relating to actors' perception and emotion is the second dimension of social capital. Nature of the ties and interaction experiences are primary causal factors of relationships (Nahapiet and Ghoshal 1998). One dominant relational factor is trust (Coleman 1988; Nahapiet and Ghoshal 1998). Research has shown that trust is positively related to actors' willingness to exchange and interact with others (Nahapiet and Ghoshal 1998) and thus facilitates the capital flows within the network. Similarly, Coleman (1988) suggested that trustworthiness is indispensable to the maintenance of social relations. When measuring consulting assets, trustworthiness should be taken into consideration.

Consulting firms: non-motivator of big data adoption

Social capital theory of innovation posits that innovation is knowledge-based and determined by the resource flows from interactions among network actors (Nahapiet and Ghoshal 1998; Maskell 2000; Molina-Morales and Martínez-Fernández 2010). Research networks, such as relationships with consulting firms, enable know-how and know-what knowledge exchanges that would have positive effects on knowledge accumulation and value creation. However, empirical studies have found insignificant effects of research networks on innovation. For example, Landry et al. (2002) found the insignificant relationship between consulting networks and the likelihood to innovate. Venkatesh et al. (2003) also found that social influence had insignificant effects on individual's intention to adopt technology.

To explain the insignificant effects of consulting ties on marketers' intention to adopt big data, we reviewed the four conditions, without which resource exchanges in social networks would not take place. The four conditions are the opportunity, the motivation, the value expectancy and the capability (Nahapiet and Ghoshal 1998). First, opportunity comes from the connection to certain network actors. Without established connections, network interactions and resource exchanges would not happen (Nahapiet and Ghoshal 1998). Moreover, Nahapiet and Ghoshal (1998) suggested that the lack of motivations and value expectancy are two prerequisites of resource exchanges in social networks. Specifically, value expectancy shows "what" actors expect from network interactions and resource exchanges, whereas motivation shows “why”. Furthermore, network actors require certain capabilities to transfer the network assets into internal assets (Nahapiet and Ghoshal 1998).

In the big data context, though connections to consulting firms bring opportunities for know-how and know-what knowledge exchanges, the value expectancy and motivations of marketers towards big data innovation are highly uncertain at the pre-adoption stage. The know-how and know-what knowledge flow from consulting firms would have few effects if individuals anticipate little value and have few motivations to adopt big data.

Moreover, the control effect of clients over consulting firms is another reason why consulting assets may have insignificant effects on clients’ intentions to adopt big data. The control effect means that actors possess a certain type of network can gain power and influence other actors. The case of the Senate Club (Coleman 1988) well exemplifies the control benefits. Senators, who have close relationships with other senators, are more influential than others because they use those relationships to control the legislations. In this case, the network ties to other senators and the obligations embedded within the network ties contribute to the particular senator’s power.

Networks rich in structural holes are associated with control benefits (Burt 2009). Structural holes exist between two indirectly connected actors (Burt 2009). Burt’s structural hole theory suggested that networks rich in structural holes provide the ego broad access to information and stronger bargaining power, leading to the control benefits over the resource flows within the networks (Burt 2009; Seibert et al. 2001). When a marketer can reach many external consultants, this marketer is in the network with structural holes and thus possesses control benefits and stronger bargaining power over the consultants.

The control benefits lead to a facilitating rather than a motivating role of social capital from consulting networks, because the networks resources are obtained and used by the focal actors to attain rather than determine their goals (Seibert et al. 2001). Deshpande and Zaltman’s study (1982) has also shown marketers’ power in deciding market research information utilization. Marketers may hold a preoccupation with the value and trustworthiness of certain relationships and exclude other possibilities. The preoccupation together with control benefits, according to the social capital theory (Adler and Kwon 2002; Ahuja 2000), constrains the information benefits and the roles of consulting networks in big data innovation.

Due to the two indeterminate conditions (value expectancy and motivations) during the pre-adoption, as well as the controlling effects of consulting ties, we predict that consulting assets derived from relationships with external consultants do not affect individuals' intentions to adopt big data. The main determinants of big data adoption remain the five attributes from innovation diffusion theory, which has held a dominant position in innovation adoption research (Rogers 1995).

Consulting firms: diffusers of big data innovation

The second stage of big data innovation process in our research is the diffusion stage, at which big data adoption has been approved at the organizational level and is diffusing among departments. As mentioned, there are four conditions without which resource exchanges with consulting firms would not happen, and they are opportunity, motivation, value expectancy and capability (Nahapiet and Ghoshal 1998). At the diffusion stage, organizational approval of big data adoption is a strong external incentive of using big data. This means that the motivation condition is met at the diffusion stage. Also, to clients, consulting assets are important sources of know-what and know-how in marketing domain, as well as performance "scripts" for solving problems in the marketing area, which have positive influences on their capabilities in knowledge combination and creation (Amabile 1983; Deshpande and Zaltman 1982;). Thus, the effect of consulting firms at the diffusion stage is contingent on clients' value expectancy.

First, the effect of consulting firms on intention to use big data is conditioned on individuals' perception of big data advantages. The main benefit of consulting networks is information benefit (Adler and Kwon 2002; Nahapiet and Ghoshal 1998). When big data is perceived as relatively beneficial, the information flows from consultant ties can reinforce the relative advantage perception, and thus would increase individuals' intentions to use big data innovation (Rogers 1995; Venkatesh et al. 2003). However, when relative advantage is perceived as low, information from consultants would reinforce the disadvantages of big data and thus individuals would not intend to use big data.

Hypothesis 3.1: When individuals perceive high-level of relative advantage, consulting assets (i.e. social capital derived from relationships with external consultants) have positive effects on their intention to use big data at the diffusion stage; when individuals perceive low-level of relative advantage, consulting assets have negative ones.

Moreover, the effect of consulting assets would be stronger when individuals have more difficulties in implementing big data innovation. According to the Rogers' (1995) innovation diffusion theory, innovation is more likely to be diffused when it is perceived as less difficult. In the big data context, marketers are more likely to use big data, when they consider big data is easy to use. Therefore, the effect of consulting firms is weaker when big data is easy to use. However, when big data is perceived as more difficult, individuals might have higher expectancy from consulting firms, because the know-what and know-how knowledge from consulting firms make it easier for marketers' use big data. The higher expectancy from consulting networks would enhance the effects of resource exchanges and value creation (Nahapiet and Ghoshal 1998). Therefore, it is reasonable to propose that when individuals perceive big data is difficult to use, high-level consulting assets would lead to more intention to use, whereas when individuals perceive big data is easy to use, they would have a high intention to use regardless of consulting assistance.

Hypothesis 3.2: When individuals perceive low-level of ease of use, consulting assets (i.e. social capital derived from relationships with external consultants) increase their intentions to use big data during the post-adoption period; when individuals perceive high-level of ease of use, they have a high intention to use big data regardless of consulting *assets.*

Similar hypotheses can be developed on the interaction between consulting assets and observability and trialability. That is, when individuals perceive low-level of observability and trialability, they tend to have higher expectancy from consulting firms. The high expectancy increases the interactions with external consultants, which provide know-what and know-how information, increase their certainty on big data performance, and thus boosts their intention to use big data. When the observability and trialability are high, individuals would intend to use big data regardless of consulting assistance. That is, the effects of consulting assets are weaker when individuals have more opportunities to observe others' use of big data or try big data.

Hypothesis 3.3: When individuals perceive low-level of observability, consulting assets (i.e. social capital derived from relationships with external consultants) increase their intentions to use big data at the diffusion stage; when individuals perceive high-level of ease of use, they have a high intention to use big data regardless of consulting assets.

Hypothesis 3.4: When individuals perceive low-level of trialability, consulting assets (i.e. social capital derived from relationships with external consultants) increase their intentions to use big data at the diffusion stage; when they perceive high-level of ease of use, they have a high intention to use big data regardless of consulting assets.

The two-way effect between information seeking and consulting assets may be considered, though there is not sufficient theory on which to develop hypotheses. The accumulation of consulting information might inform clients about the compatibility of big data and thus lead to more intention to use big data. Alternatively, clients that are open to new information might have other information channels. And interactions with consultants might slow down or even intervene the decision-making process, and thus lead to low intention to apply big data innovation to extract insights from customer data. On net, there is no hypothesis made on how information seeking may interact with consulting assets at the diffusion stage.

Consulting firms: facilitators of big data usage

As stated in the previous part, organizational approval of big data becomes an important external incentive of using big data analytics at the diffusion stage, and individuals' value expectancy of big data is moderated through the interactions and resource exchanges with consulting firms. We define the following stage as implementation stage, at which marketers are more certain with the potential outcomes of big data and decide whether to use big data. In the implementation stage, consulting firms have direct facilitating effects on the usage of big data through providing know-how and know-what knowledge, as well as other technical supports.

In social capital theory, one direct effect of social capital is information (Adler and Kwon 2002; Nahapiet and Ghoshal 1998). Social capital arises because of the network structure of actors, and the existing network ties can be viewed as information channels, which allow access to other actors and facilitate the exchange and combination of information. The interactions and resource exchanges with consulting firms enhance marketers' knowledge accumulation and improves clients' capability to use big data. First, these consulting networks act as channels of know-what and know-how information, which is needed for the innovation implementation (Landry et al. 2002; Tsai and Ghoshal 1998). In other words, consulting assets can be transformed into local knowledge and contribute to focal actors' intellectual asset accumulation (Nahapiet and Ghoshal 1998; Tsai and Ghoshal 1998). Second, consulting assets can be transformed to marketers' capability, assisting the understanding and implementation of big data innovation. On one hand, marketers can learn from consultant through frequent interactions and communications. On the other hand, consultants can directly offer solutions when marketers have difficulties. Therefore, by connecting to consulting firms, marketers can transform the know-how and know-what knowledge to internal resources and capabilities, facilitating the use of big data. Hence, it is reasonable to predict that social capital derived from consulting ties directly facilitates marketers' use of big data.

Hypothesis 3.5: Consulting assets (i.e. social capital derived from relationships with external consultants) facilitate the actual usage of big data innovation at the implementation stage.

Methods

In this research, we collected data through 21 face-to-face interviews and 337 questionnaires to examine the effects of social capital embedded within consulting networks on big data adoption process. Interviews were conducted to pre-test our hypothesis and to assist the design of questionnaires

The questionnaires, from 337 marketing professionals are used to build quantitative models for marketers' intention to adopt big data, intention to use big data during the diffusion period and the actual usage at the implementation stage. All of the respondents answered the questions concerning the pre-adoption period, but a subset of 149 respondents, who were current users of big data analytics, answered questions of the diffusion and implementation stage. The data collection process and sample characteristics were shown presented in Chapter 2.

Pilot test

In-depth interviews were conducted to pre-test our hypotheses, and information of interviewees was provided in our previous research (see Study 1 in Chapter 2).

Interview findings strengthened our hypothesized effects of consulting firms on marketers' intention to adopt and use of big data innovation. Social capital resulted from frequent interactions with consultants are not essential in the decision to adopt big data. However, after the adoption decision is made, external consultants will be brought in to facilitate the implementation of data analytics. For example, one strategy manager from a telecommunication organization suggested that external experts (such as data warehouse architects) were not involved in the adoption decision process, but were hired after the adoption to assist the project implementation. This finding was consistent with that of another consultant we interviewed. He suggested that when the adoption decision is made, external consultants will be hired to facilitate the analytics implementation, supported our hypotheses of the facilitating role of consulting firms.

Results

To test the hypotheses, six independent constructs and three dependent constructs were measured. A questionnaire was designed based on previous research and the face-to-face interviews conducted in another stage of this research (see Study 1 in Chapter 2).

Independent variables

This study used 24 items to measure the six independent constructs. Social capital embedded within consulting networks was measured from three dimensions, including interaction frequency, trust and importance (Paxton 1999; Tsai and Ghoshal 1998). Follow previous studies on social capital, we measured frequencies with a scale from “never” (0) to “always” (5), measured trust with the scale from “none” (0) to “very high” (5), and measured the importance of the ties with a scale from “not at all important” (-3) to “extremely important” (+3) (Paxton 1999; Tsai and Ghoshal 1998). Additionally, items for perceived attributes of big data were borrowed from our previous study (see Study 1 in Chapter 2).

Factor loadings and Cronbach’s alphas of independent constructs are shown in Table 3.1. All items loaded on expected constructs, and 64 percent of the variance was explained. Nineteen loadings had absolute value above .80, and one loading was above .70. Items of observability did not load on one factor, which is consistent with the complex nature of big data innovation. And so we dropped observability in the following analysis. The reason has been discussed in Chapter 2.

Dependent variables

We adapted three constructs from individual acceptance of technology theory to measure marketers' *intention to adopt* big data, *intention to use* big data at the diffusion stage and *actual usage* at the implementation stage (Davis et al. 1992; Venkatesh et al. 2012). Capturing big data adoption behavior with the three sequential variables allows us to compare the effects of consulting firms at different stages of big data innovation process, and so further examine whether social capital from consultants is a motivator, diffuser or facilitator in the innovation process. The factor loading matrix and Cronbach's alpha of the three dependent variables are presented in Chapter 2.

Findings

Generalized linear model (GLM) was used to predict big data adoption variables. Independent and dependent variables were centered and scaled prior to analysis. The models fit well, explaining 61 percent of the variance for intention to adopt big data, 79 percent of the variance for intention to use big data at the diffusion stage and 55 percent of the variance for the actual usage at the implementation stage (Table 3.2).

One-way effects of innovation attributes were highly consistent with previous research (see Study 1 in Chapter 2). Relative advantage had significant effects on both intention to adopt big data ($\beta = .61, p = .0000$) and intention to use big data ($\beta = .45, p = .0000$), but had an insignificant effect on the actual usage. Ease of use had a significant one-way effect on intention to use big data at the diffusion stage ($\beta = .20, p = .0163$), and information seeking (i.e. compatibility) had a significant one-way effect on the actual usage($\beta = .20, p = .0026$). Additionally, trialability had significant effects on intention to adopt($\beta =.33, p = .0000$), intention to use ($\beta = .27, p = .0003$) and the actual usage($\beta = .32, p = .0026$).

Consulting assets not affecting intention to adopt big data. Results showed that the effect of consulting assets was not significant on intention to adopt big data during the pre-adoption period. That is, social capital from consulting networks does not affect big data adoption decision during the pre-adoption period.

Table 3.1 ***Cronbach's Alpha and Factor Loading Matrix for Independent Variables (Study 2)***

Items	**Information seeking** (*i.e.* Compatibility)	**Relative advantage**	**Ease of Use** (*i.e.* the reversal of Complexity)	**Trialability**	**Consulting assets**
I regularly explore information about markets.	**0.800**	0.199	0.134	0.186	0.215
I often seek out information about new customer behavior trends.	**0.859**	0.202	0.135	0.163	0.086
I frequently search for information about new ways to understand customers and markets.	**0.897**	0.178	0.107	0.219	0.192
I actively look for information about new methods to understand consumers.	**0.894**	0.228	0.147	0.202	0.211
Big data analytics gives me great insights into market & customer changes.	0.231	**0.887**	0.506	0.294	0.188
Big data analytics enables me to gain insights into consumers more quickly.	0.221	**0.860**	0.440	0.295	0.133
Big data analytics improved/improves the quality of my understanding of markets and customers.	0.176	**0.895**	0.524	0.271	0.144
Big data analytics makes it easier to understand consumers.	0.195	**0.885**	0.511	0.321	0.168
I believe that it is easy to use big data to do what I want it to do.	0.172	0.480	**0.913**	0.474	0.166
Learning to operate big data system is easy for me.	0.128	0.497	**0.918**	0.507	0.125
How I would interact with big data is clear and understandable.	0.139	0.558	**0.948**	0.494	0.119
Overall, I believe that big data is easy to use.	0.125	0.533	**0.925**	0.490	0.141
I am permitted to use big data on a trial basis long enough to see what it could do.	0.243	0.319	0.510	**0.898**	0.149
Before deciding whether to use big data, I have many opportunities to try various big data approaches.	0.163	0.304	0.447	**0.924**	0.157
Before deciding whether or not to use big data, I am able to properly try out big data solutions.	0.230	0.361	0.486	**0.932**	0.177
Big data solutions are available to me such that I could adequately test run various applications.	0.219	0.263	0.468	**0.930**	0.142
I know where I can go to satisfactorily try out various uses of big data.	0.160	0.270	0.498	**0.865**	0.088
Frequency of interaction with consulting firms	0.184	0.154	0.147	0.189	**0.892**
Trust of consulting firms as sources of customer information	0.154	0.126	0.122	0.109	**0.771**
Importance of consulting firms as sources of customer information	0.188	0.175	0.112	0.098	**0.896**
Cronbach's alpha	**0.885**	**0.905**	**0.945**	**0.948**	**0.819**

Note: Principle components factor analysis with Varimax rotation was used. Boldface indicates significant loadings.
N=337

Table 3.2 ***Generalized Linear Model Results predicting Big Data Adoption Behaviors (Study 2)***

	Adoption		Diffusion		Implementation	
	Intention to adopt		Intention to use		Actual Usage	
	Estimates	Pr(>|t|)	Estimates	Pr(>|t|)	Estimates	Pr(>|t|)
(Intercept)						
Big data innovation attributes						
Relative advantage	.61	=.0000	.45	=.0000		
Ease of use (i.e. the reversal of Complexity)			.20	.0163		
Information seeking (i.e. Compatibility)			.07	.1229	.20	.0026
Trialability	.33	=.0000	.27	.0003	.32	.0026
Social capital						
Consulting assets			-.00	.9570	.18	.0043
Intention to adopt	N/A		N/A		.36	.0032
Interactions						
Relative advantage × Consulting assets			.30	=.0000		
Information seeking × Consulting assets			-.13	.0008		
Ease of use × Consulting assets			-.12	.0396		
Adjusted R^2		.61		.79		.55
Number of respondents		337		149		149

Consulting assets affecting intention to use big data. Hypothesis 3.1 suggested that individuals with a higher-level of consulting assets have more intention to use new-adopted big data innovation at the diffusion stage when the relative advantage of big data is high; but when relative advantage is low, high-level of consulting assets would result in low intention to use. Results showed that consulting assets had a significant two-way interaction $(\beta = .30, p = .0000)$ with relative advantage in the intention to use big data model (Table 3.2).

Following the method of Aiken et al. (1991), we plot the interaction between consulting assets and relative advantage (Figure 3.1a). To construct the figure, high-level of consulting assets was defined as one standard deviation above the mean, and low-level of consulting assets was defined as one standard deviation below the mean. The high-level and low-level of relative advantage were defined similarly. The values of y-axis in the figures are the predicted values of each dependent variable in each situation.

As shown in Figure 3.1a, consulting assets have positive effects on intention to use big data when relative advantage is high. That is, when marketers perceive high-level advantages from big data, the information flows from consulting firms specifies and reinforces the perception and thus increases marketers' intention to use big data. However, when relative advantage is perceived as low, information from consultants reinforces marketers' negative perception and discourages their intention to use big data. Thus, Hypothesis 3.1 was supported.

Figure 3.1a. Relative advantage affecting relation between consulting assets and intention to use

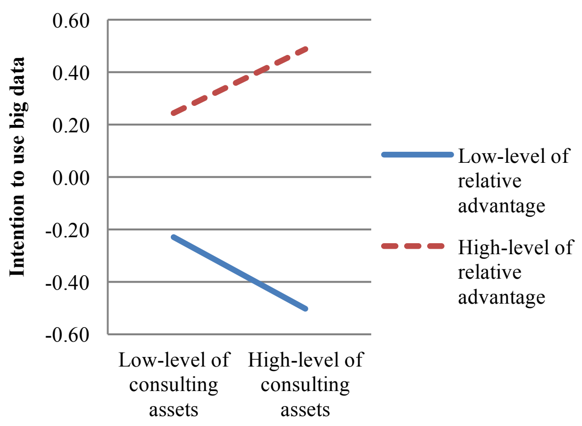


Figure 3.1b. Ease of use affecting relation between consulting assets and intention to use

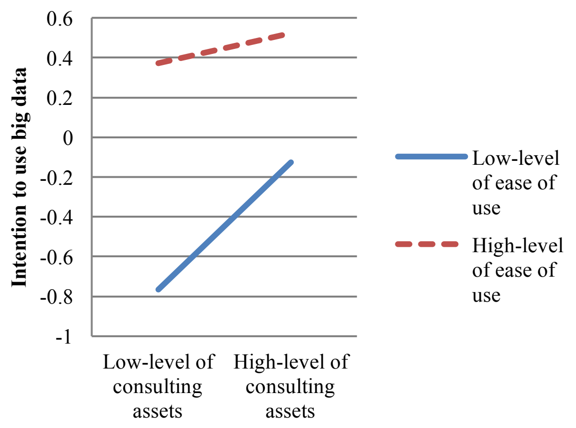
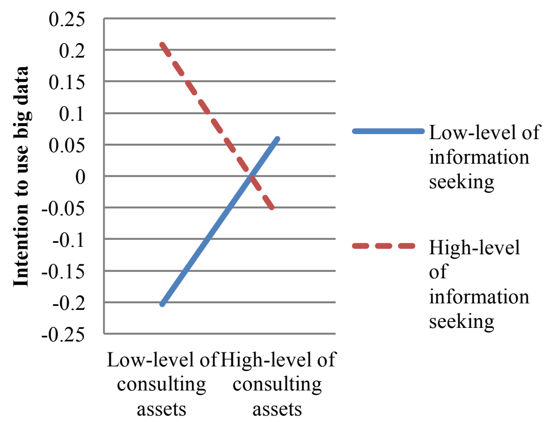


Figure 3.1c. Information seeking affecting relation between consulting assets and intention to use



Hypothesis 3.2 suggested that when big data is perceived not easy to use, high-level of consulting assets would increase marketers' intention to use. Results showed the interaction

between ease of use and consulting assets was significant $(\beta = -.12, p = .0396)$. The steeper upward line of low-level of ease of use in Figure 3.1b demonstrated the positive effect of consulting assets on intention to use big data when big data is difficult to use. Thus, Hypothesis 3.2 is supported.

The observability construct was dropped in the factor analysis and the interaction between trialability and consulting assets were not significant. Thus, Hypothesis 3.3 and 3.4 were not supported.

Results showed that the interaction between information seeking and consulting assets had significant effects on intention to use big data $(\beta = -.13, p = .0008)$. Following the same method, we mentioned above (Aiken et al. 1991), we plot interaction between information seeking and consulting assets (Figure 3.1c). The downward line of high-level of information seeking showed the negative relationship between consulting assets and intention to use big data when information seeking is low. When marketers are constantly seeking new information, consultants might be a negative force that slows down marketers' speed through providing extra information, or even confuse or discourage marketers through providing inconsistent information.

Consulting assets affecting the usage of big data. Results showed that consulting assets had direct and positive effects on big data usage at the implementation stage $(\beta = .18, p = .0043)$. That is, the know-how and know-what knowledge from consulting firms directly facilitate the use of big data at the implementation stage. Therefore, Hypothesis 3.5 is supported.

Discussion

Theoretical contribution

A systematic literature review suggested that social capital benefits innovation adoption in a complex way. We investigated the effects of consulting assets, the social capital from consulting networks, on three sequential steps of big data innovation, namely the adoption, diffusion and implementation.

Our findings enrich the innovation literature by unveiling the varying roles of social capital in different stages of the innovation process. Theoretically, social capital is identified to be important source of innovation (Nahapiet and Ghoshal 1998). However, empirical findings on the relationship between social capital and innovation were inconsistent (Landry et al. 2002; Tsai and Ghoshal 1998). We thus proposed that social capital may not have unvarying effects throughout the innovation process, and effects of social capital is not always beneficial. Our findings supported our hypotheses by demonstrating the varying roles of consulting firms at three steps of big data innovation. Specifically, we found that consulting assets have diffusing and facilitating effects on big data innovation, rather than the motivating effects. The R-square from .55 to .79 showed a high-level goodness of fit of the models. Our findings resolved the conundrum of roles of social capital in innovation adoption process by demonstrating when social capital matters in big data innovations.

We add to the individual acceptance of information technology theory, which attempts to examine the effects of social influence on users' adoption of new information technology. Venkatesh et al. (2003) demonstrated that social influence had no significant effects in technology adoption and usage, though the relationship has been recognized in theoretical research. In contrast to previous work (Venkatesh et al. 2003), we attempted to pinpoint the position of social capital in individual acceptance of information technology theory by measuring the effects of consulting firms, rather than measuring social influence generally. Social capital can have varying benefits (Adler and Kwon 2002; Nahapiet and Ghoshal 1998; Portes 1998) and thus examine the effects of social capital as a whole might not be effective. In line with social capital theory, we contribute to the individual acceptance of information technology theory by demonstrating the roles of one specific form of social capital (namely consulting assets) in three sequential steps of big data innovation and provide empirical evidence to justify our hypotheses.

This research also makes a distinctive contribution to market research adoption literature.

Research has shown interactions between market researchers and marketers encourage the research adoption (Deshpande and Zaltman1982; Moorman, Zaltman and Deshpande 1992). On top of existing research on market research adoption, we examined the effects of interactions between marketers and consultants on marketers' adoption intention and usage over time. We add to the use of market research theory that interactions with consulting firms have facilitating effects rather than motivating effects on the use of market research.

Lastly, by applying social capital theory into innovation research, this study has generalized effects of social capital in the marketing area. That is, in addition to social actions, the social capital theory is a viable theory to study innovation within social organizations. Our research provides empirical findings to the relationship between social capital and the adoption behavior in the context of big data innovation for marketing decisions.

Managerial implications

Given the continuously changing market, marketers are supposed to be proactive in improving marketing analytics to understand markets and customers. And consulting firms, especially market research firms, play an important determining role in marketing analytics innovation diffusion. This is supported by prior market research adoption literature (Deshpande and Zaltman 1982). However, our findings suggest that social capital resulted from consulting networks plays a facilitating role after innovation is adopted, rather than a motivating role. That is, interactions with consultants do not increase marketers' motivation to adopt certain innovation, but when marketers have decided the adoption, consultants will be hired to assist the implementation of innovation. For example, a big data consultant suggested that their clients usually come with a decision that has been made and seek assistants in the implementation of the decision.

As shown in Figure 3.2a, social capital from consulting relationships enlarge the relationship between relative advantage and marketers' intention to use big data during the post-adoption period. This reinforces the facilitating role of consulting ties. When marketers' perceive high-level of relative advantage from big data innovation over the previous marketing analytics, interactions with consultants would increase marketers' intention to use big data innovation. However, when big data innovation is perceived with low benefits, marketers would not intend to use it regardless of what consultants suggest.

Also, the facilitating role of consulting ties is more effective when marketers face difficulties in applying big data analytics. When the complexity of big data innovation is low, marketers would use big data regardless of consulting assets. But when big data is perceived as difficult or when marketers are unsure about the potential performance of big data innovations, information from external consultants would be critical in facilitating the use of big data.

Limitations and directions for future research

Although we applied multi-method and collected data from both big data prospects and users to examine the roles of social capital, the research may have following limitations that actual usage of big data innovation is self-assessed, and that intention to adopt big data is retrospective. However, we have conducted a t-test to examine the difference of intention to adopt big data assessed by big data users and big data prospects. Results showed that there is no significant difference between the intention to adopt big data by users and prospects. Thus, the current research is less likely to be suffered from the retrospective issue.

In this research, we have discovered the diffusing and facilitating effects of social capital from consultant relationships on big data innovation at the diffusion and implementation stages. Further research can investigate which type of social capital might affect innovation adoption during the pre-adoption period. In addition, future research can investigate the conditions under which the effects social capital on innovation adoption would work.

In conclusion, this study investigates how social capital from consulting relationships affect big data adoption behaviors at three sequential steps of big data innovation process. Data from 149 big data users and 188 potential adopters were collected to examine the effects of consulting assets. Results suggest that social capital from consulting relationships do not affect individuals' intentions to adopt big data during the pre-adoption period. Rather, the effects of consulting assets are more significant on individuals' intentions to use big data at the diffusion stage, and on actual usage of big data at the implementation stages, showing a facilitating rather than motivating role of consulting firms in big data innovation.

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CHAPTER 4: BIG DATA PERFORMANCE: THE STRATEGY-EXECUTIVE-PERFORMANCE FRAMEWORK

Abstract

Though the strategic importance of big data is well recognized, few theories have been established to explain data analytics performance. We developed a strategy-execution-performance framework to explain big data analytics performance. This framework was tested with pair datasets containing 200 questionnaires from 16 organizations that were using big data, and 78 assessments from 15 external consultants. Results showed that big data performance had 55 percent of variance explained by big data execution variables, including evaluation and data-driven decision. Big data execution process was significantly affected by organizational strategic responsiveness, as well as two contextual factors (i.e. centralization and competition intensity).

Introduction

Turning big data into valuable results has appeared on the top of organization agenda (Barton and Court 2012; Bughin, Livingston and Marwaha 2011; McAfee and Brynjolfsson 2012). For example, Facebook partners up with IBM to extract customer insights from the massive data Facebook holds (Bort 2015). Ian Narev, Chief Executive Officer of Commonwealth Bank of Australia, considers big data analysis as a top priority (Eyers 2014). However, empirical difficulties are compelling, as merely 10 percent of organizations succeed in data analytics (Davenport et al. 2001)

The major question has become how to achieve masterful big data performance. Researchers and practitioners have offered several suggestions. One most commonly mentioned suggestion is that technologies and talents are necessary for big data analytics. McAfee and Brynjolfsson (2012) suggest that organizations require advanced technologies such as Hadoop to integrate, store, and process big data. Some others suggest that organizations also require talented data scientists to build advanced analytical models to turn data into valuable insights (Barton and Court 2012; Brown, Chui and Manyika 2011).

Another common suggestion is to build the right strategy and organizational contexts for big data analytics (Barton and Court 2012; Bughin et al. 2011; Davenport 2007; Davenport et al. 2001). For example, some researchers suggest a clear strategy directs analytical resources allocation and deployment (Barton and Court 2012; Bughin et al. 2011; Davenport et al. 2001). Moreover, a right organizational structure enables the cross-functional cooperation among executives, business analysts and technicians and thus improves the quality of analytical results (Barton and Court 2012; Bughin et al. 2011; Davenport et al. 2001).

A third common suggestion involves the execution process. Davenport et al. (2001) suggest that insights from data affect organizational policies through a transformation process, especially the data-driven decision process. Data would not lead to valuable results if decision makers do not use analytical results in the decision process, or execute only insights that meet their expectations. Consistently, McAfee and Brynjolfsson (2012) indicated that data-driven decisions lead to better decision results.

Despite the pervasiveness of these assertions, empirical research is needed to examine the external validity of their suggestions and guide to what extent these factors (i.e. the strategy and the execution process) underpin big data performance. Indeed, no real theory has been established to explain previous data analytics innovations, such as scanner data analytics. Research on scanner data mainly focuses on the technical aspects (Bucklin and Gupta 1999). Few studies explain how to achieve high performance of scanner data analytics. Moreover, research on big data analytics is rather qualitative and fragmented (Barton and Court 2012; Brown et al. 2011; Bughin et al. 2011; McAfee and Brynjolfsson 2012). Few empirical studies have yet investigated big data performance. For example, Davenport et al. (2001) established a data-knowledge-result process to explain data analytics, which however has not been quantitatively tested yet. The lack of theoretical framework and empirical test call for further research into which factor underpins data analytics performance.

This study established a strategy-execution-performance framework and quantitatively tested the effects of the commonly mentioned factors (e.g. strategy, centralization, data-driven decisions etc.) on big data performance. We proposed that big data performance is dependent on the execution process including the big data evaluation process and the rational data-driven decision process. We also proposed that the execution process is contingent on organizational contextual factors, including strategic responsiveness, centralization and competition intensity. We did not include the investment on technology and talent into our framework though it is one most commonly mentioned factors underpinning big data analytics. The reason is that investments on building the big data warehouse, analytical tools and dashboards and hiring talented data scientists are necessary but not sufficient to big data performance. Studies have shown that most organizations have made necessary investments in data analytics, but these investments did not guarantee positive analytics success (Davenport 2007; Davenport et al.

2001).

Firstly, we proposed that the execution process is significantly correlated with organizational strategic responsiveness. Being strategic responsive, organizations requires a proactive evaluation of external competition dynamics and adapt strategy accordingly (Bughin et al. 2011; Davenport et al. 2001; Ketchen 2004). Strategic responsive organizations are more likely to value and use the information of internal and external factors in the decision process (Bughin et al. 2011; Davenport et al. 2001). While strategic responsiveness is the main predictor, competition intensity and centralization are two moderating contextual variables in our strategy-execution-performance framework. Centralization might weaken the positive effects of strategic responsiveness on the data-driven decision process. In centralized organizations, though decision makers are strategic responsive, information might be distorted or blocked when passed from one level to another (Deshpande 1982). But when organizations are facing high competition intensity, centralization might lead to more data-driven decisions.

Secondly, we proposed that the execution process is significantly correlated with big data performance. A thorough evaluation of big data is an important process when executing big data strategy. The thorough evaluation of environments and internal capabilities generates knowledge, reduces uncertainty and leads to rational decisions (Ketchen et al. 2004; Priem et al. 1995; Schweiger, Anderson and Locke 1985). According to decision science literature, rational decision process has direct positive effects on firm performance (Priem et al. 1995; Ketchen et al. 2004). Executing big data strategy also requires data-driven decisions. Without using data in the decision process, the potential of data cannot be transformed into valuable results (Davenport et al. 2001). We proposed that it is the execution process links the big data strategy and the performance, transforming big data into valuable results.

To test the strategy-execution-performance framework, we collected 200 questionnaires from 16 organizations. To minimize common-method bias, we also invited 15 external consultants to evaluate the big data performance of the 16 organizations and obtained 78 external big data performance assessments. Our findings significantly support the strategy-execution-performance framework.

In the following sections, we first review existing research on organizational contexts, decision process theory and big data performance, based on which we developed the strategy-execution-performance framework. Next, methodology and samples are presented. Lastly, findings, theoretical and managerial implications, and further research are discussed.

Theory Development

To achieve analytics success, analytics researchers have recognized the importance of strategy and organizational contexts (Bughin et al. 2011; Davenport 2007; Davenport et al. 2001), as well as the analytics execution process (Davenport et al. 2001). First, the analytics execution process, especially the decision use of analytics results is indispensable in transforming valuable insights into effective decision results (Davenport et al. 2001). The pre-evaluation process, a critical process in the strategic decision process (Fichman and Kemerer 1997; Ketchen 2004), educates organizations on the potential of big data analytics to avoid inefficient decisions. Second, the analytics execution process is underpinned by strategic responsiveness to the changing market, organizational structure and competition intensity. The explanatory variables in this research were those commonly mentioned variables in analytics literature. To understand the effects of these variables, we include two control variables (e.g. industry and city) in our framework. In this section, we reviewed the dynamics among strategy responsiveness, execution process and big data performance, as well as the moderating role of two contextual factors, centralization and competition intensity. Based on the review, a strategy-execution-performance framework was developed.

Big data execution and performance

Big data performance. How to seize the potential of big data has been the center of attention (Barton and Court 2012; Brown et al. 2011; Bughin et al. 2011; McAfee and Brynjolfsson 2012). Theoretically, the outcomes of data analytics are threefold, behaviors, process and program, and financial performance (Davenport et al. 2001). That is, the value, such as customer insights, extracted from data affects organizational behaviors, alters business process and programs, and ultimately improves business profitability. In this research, we define big data performance by the degree to which the potential value of big data is achieved by organizations.

Investments in big data technologies are suggested as ways of exploiting big data (Bughin et al. 2011; McAfee and Brynjolfsson 2012). However, the monetary investment is necessary but hardly sufficient. Davenport et al. (2001) have provided a number of examples of organizations investing massively on ERP system, customer relationship management system, scan panel data technology and some other related technologies. Of these companies, less than 10 percent succeed in turning data into valuable results (Davenport et al. 2001). It is obvious that monetary investment and technology do not guarantee the analytics success.

Davenport et al. (2001) have recognized that the execution process such as data-driven decision is essential to data analytics performance. Consistent with this view, strategic decision process researchers suggest that rational decision process has positive effects on organizational performance (Ketchen 2004; Priem et al. 1995; Schweiger et al. 1985). A rational decision process should include a thorough pre-evaluation process to collect information and identify external opportunities, as well as the use and execution of data analytics in the decision process, transforming data into decision results (David 2011). Accordingly, we adopted the pre-evaluation of big data analytics and the decision use of analytics results to capture big data analytics execution process, and reviewed the dynamics between the big data analytics execution process and big data performance.

Pre-evaluation of big data analytics. Pre-evaluation is an important step in the decision-making process (Fichman and Kemerer 1997; Ketchen 2004). A thorough evaluation of environment allows decision makers to gather relevant and sufficient information for analysis, identifying opportunities, forming the strategy and making decisions (David 2011).

The pre-evaluation process affects the comprehensiveness and quality of the inputs into decision-making process. In this research, we define the pre-evaluation of big data analytics as the trial process of big data, based on which organizations can gain insights into the relative advantage, complexity and compatibility of big data analytics.

Pre-evaluation of big data and big data performance. To improve big data performance, a precondition is that there is a potential value of using big data. Due to the existence of managerial fads and fashions, organizations sometimes adopt potentially inefficient innovations or reject potentially efficient innovations (Abrahamson 1991). The purpose of the pre-evaluation of big data is to gather information for analysis and identify the potential advantages and disadvantages of adopting and using big data analytics. First, pre-evaluation provides information for rational analysis and decisions (Jocumsen 2004). Through a thorough evaluation of big data, organizations can recognize the relative advantages, complexity, compatibility and other attributes of big data analytics. With the evaluation of big data attributes, the adoption decision is more rational and the potential performance is more predictable and controllable. Moreover, a thorough evaluation of big data educates organizations about the problems big data can resolve, and the process, resources and capabilities underpinning big data analytics. With this knowledge, decision makers can develop the plan, allocate analytical resources and build analytical capabilities to transform big data into valuable results. It is reasonable to predict a positive relationship between the pre-evaluation of big data and big data performance.

Hypothesis 4.1: The thorough pre-evaluation of big data analytics underpins organizational big data performance.

Decision uses of analytics results. Decision uses of analytics results depicts the data-driven decision process turning data into decision results (Davenport et al. 2001). In this research, we distinguish the use of analytics results in the decision process from decisions behaviors that are based on intuition or other irrelevant and irrational factors. We capture the decision use of analytics results by the degree of insights extracted from big data analytics are used to support decision-making. Big data and the insights extracted from big data would not affect organizational performance unless they are used in making decisions (Davenport et al. 2001). That is, the use of analytics results in the decision process is a critical link between data and outcomes.

Decision uses of analytics results and big data performance. Using data analytics to support decision is one indispensable process from data to performance (Blattberg and Hoch 1990; Davenport et al. 2001). The potential of big data would not be achieved if the decision makers do not use the insights from big data when they make decisions. Political non-acceptability of the analytical results might be one major threat to the rationality of decision (Deshpande and Zaltman 1982; Weiss 1977 & 1980). Some decision makers are likely to present and use information that meets superiors' expectations and disregard the objective truth. When the decision is not based on analytical results but political acceptability, weak rationality of decision results might decrease the performance (Priem et al. 1995).

Moreover, the use of analytical results in the decisions reflects the quality and actionability of insights from big data. According to the information usage literature, the use of information by decision markers is significantly dependent on the quality and the implementability of the information (Weiss 1977 & 1980; Deshpande and Zaltman 1982). Not all of the insights from data analytics are valuable and implementable. Managers tend to selective use of the research result based on its quality and actionability. More data-driven decisions reflect the high quality and actionability of insight inputs. Better data inputs generate better decision outputs, which improve organization performance to a considerable extent. Thus, it is reasonable to predict that data-driven decision process is positively related to big data performance.

Hypothesis 4.2: The use of analytics results in the decision process is positively related to big data performance.

Strategy responsiveness, organizational contexts and execution process

Analytics researchers have emphasized the importance of a right strategy to guide analytics activities (Bughin et al. 2011; Davenport 2007; Davenport et al. 2001). The right strategy sets the analytics direction for organizations, guiding analytics execution such as resource allocation and usage. Strategic literature also indicates that a good strategic fit, which enables firms to match up with the environment, yields better performance (Andersen, Denrell and Bettis 2007). To form a right strategy in the turbulent environment, organizations should improve their strategic responsiveness capability (Ansoff et al. 1993; Hudspeth 2004).

Strategic responsiveness. Strategic responsiveness refers to the organizational capability in proactively adapting its strategy to the changing environment (Ansoff et al. 1993). Strategy responsiveness captures the degree to which an organization is able to form a right strategic direction and effectively adapt its products and services to meet the changing demands of markets (Hudspeth 2004). In this rapidly changing environment, strategy formation is a dynamic process, rather than static one. Every strategic move in markets could be fatal. To maintain competitive advantage, organizations should improve strategic responsiveness capability, and quickly and proactively react to environment changes, such as the threat of new entrants and substitutes, changing customer behaviors and competitors' strategic moves (Ketchen 2004).

To be strategically responsive, organizations must learn at a rate faster than the rate at which environment changes (Ansoff et al. 1993; Hudspeth 2004). The fast learning rate distinguishes strategic responsive organizations from those that are passive in adapting their strategy to the environmental turbulence. Passive organizations only move after they have confronted environment changes. Strategic actions are often taken when these passive organizations see dropping profits or increasing churn. Organizations with low responsiveness to the changing environments can also be related to those reactors, who only passively adapt their strategies (Miles et al. 1978). These reactors lack systematic response mechanisms and thus cannot react appropriately and efficiently to the changing environment (Miles et al. 1978). The reasons of the lack of strategic responsiveness might be the unclear strategy articulation from the top management team, the inefficient organizational structure and process, or the unwillingness to change. Compared with the reactors, the strategic responsive organizations are more likely to seize the potential of environmental turbulence and avoid potential loss (Hudspeth 2004).

Strategic responsiveness is related to market orientation but has a different focus. Market orientation focuses on the generation of marketing intelligence, and integrates and executes it into decision-making process (Gray et al. 1998; Matear et al. 2002), whereas strategic responsiveness captures organizational capability on adapting its strategy to the changing market. Market orientation examines organizational attitudes and activities on understanding and reacting to market changes, but does not reflect the organizational capability on translating market intelligence into effective actions (Gray et al. 1998). Strategic responsiveness, however, reflects organizational capability by capturing the outcomes, namely to what extent the organizational strategy is responsive to the changing market.

Hudspeth's view (2004) suggested that strategic responsive organizations are more likely to have the strategic evaluation process, through which information of environmental changes is gathered. Strategic responsive organizations are more likely to sense the potential benefits of new systems (e.g. Ko et al. 2008; Wierenga et al. 1999). Strategic responsive organizations are not only capable of sensing environment turbulence without delay, but also capable of matching internal capabilities and resources with external opportunities and threats to keep a right strategic direction (Ansoff et al. 1993; Hudspeth 2004). Strategic responsive organizations cannot achieve these capabilities without considerable emphasis on scanning and evaluating both external and internal factors. That is, the strategic evaluation process is a necessary routine for strategic responsive organizations to learn about turbulent environment and seize the potential.

Similarly, in the big data context, a strategic responsive organization is more likely to sense the big data opportunities, and to initiate the evaluation to learn about big data analytics. A thorough evaluation provides organization relevant information on compatibility and potential outcomes of big data, which is needed to decide whether big data might be a source of competitive advantage. It is reasonable to propose that organizations with high strategic responsiveness are more likely to initiate and conduct the evaluation of big data.

Hypothesis 4.3: Strategic responsiveness to the changing market encourages the pre-evaluation of big data analytics to gather information and identify potential opportunities.

Moreover, organizations with higher strategic responsiveness are more likely to have data-driven decisions. For example, Ko et al. (2008) found that defenders and reactors had significantly low level of CRM technologies usage compared with analyzers and prospectors. Strategic responsive organizations understand that competitive advantage comes from the right strategy, and the strategy is right when information of external and internal factors are carefully gathered and evaluated (Ketchen 2004). The respect to information reflects the emphasis on rational decision-making process. Therefore, it is reasonable to propose that strategic responsiveness increases the usage of analytics insights in the decision-making process.

Hypothesis 4.4: Strategic responsiveness to the changing market underpins the use of big data analytics result in the decision process.

Furthermore, organizational structure plays an important role in big data context (Brown et al. 2011; Barton and Court 2012; Davenport et al. 2001). Organizational structure determines the roles of and cooperation among managers, business analysts and technicians, affecting the quality and actionability of the analytical outputs.

Centralization. One major dimension of organizational structure is the distribution of power in making decisions. The dominant construct in literature is centralization (e.g.

Davenport et al. 2001; Deshpande 1982; Deshpande and Zaltman 1982). Centralization captures the degree to which power in making decision is consolidated under a central control. In a decentralized organization, decision is based on census (Davenport et al. 2001; Deshpande 1982; Deshpande and Zaltman 1982). Managers, business analysts, and other technicians have more opportunities to participate in the decision-making process in a decentralized context than in centralized one.

Competition intensity. In the decision science theory, competition intensity is a major contextual factor affecting decision performance (e.g. Ketchen 2004; Priem et al. 1995). Competition intensity reflects the stability of competition environment (Priem et al. 1995). In this research, we define competition intensity as the degree to which big data competition environment changes. Competitors' strategic moves, such as new product release and promotion, can change competition structure and require quick reactions.

The direct effect of centralization on big data decision process is hardly predictable given limited relevant literature. On one hand, big data platform is an enterprise-wide platform, which is more appropriate for centralized organizations (Bughin et al. 2011; McAfee and Brynjolfsson 2012). On the other hand, a centralized power limits the non-management's participation in the decision process (Davenport et al. 2001). On net, there is no hypothesis on the relationship between centralization and decision process variables.

However, centralization might moderate the relationship between strategic responsiveness and execution process variables. As stated before, strategic responsiveness leads to more data-driven decisions. In centralized organizations, though decision makers are strategic responsive, information is likely to be distorted or blocked through the low-level to top-level management team (Deshpande 1982). One major reason for the information distortion is the individual differential selective perception of information (Deshpande 1982). Since individuals interpret information in different ways, information is distorted as it flows from the bottom to the top of the hierarchy. Moreover, information distortion and blockage might happen when employees intend to present only the information that meets superiors' expectation (Deshpande 1982). Under this circumstance, though decision makers in centralized organizations intend to form strategies based on objective and relevant information, information distortion and blockage might pose a threat to the data-driven decision process. Therefore, it is reasonable to predict that the effect of strategic responsiveness on the data-driven decision is weaker in centralized organizations.

Hypothesis 4.5: Centralization weakens the positive relationship between strategic responsiveness to market changes and the use of analytics results in the decision process.

According to decision process theory, competition intensity might lead to more data-driven decisions (Ketchen 2004; Priem et al. 1995). Competition intensity is resulted from the lack of differentiation among existing competitors. In such industry, every strategic move of competitors might threaten organizational profitability. To survive in the intense competition, organizations should actively scan the environment, analyze competitors' moves and adapt strategies (Ketchen 2004).

The effect of competition intensity is stronger when the organization is centralized. When the organization is highly centralized, decision makers bear almost all responsibilities. To reduce the risks coming along with the intense competition, decision makers would try to collect as much information as possible to reduce uncertainty and make sound decisions. That it, in centralized organizations, when decision makers perceive more competition intensity, they are more likely to gather data and information to learn about markets and competitors and to support decision-making process.

Hypothesis 4.6: Centralization strengthens the effects of competition intensity on the use of analytics results in the decision process.

Methods

To examine our hypotheses, we collect both internal and external assessments on 16 organizations with pretested questionnaires. The 16 organizations were from a pool of organizations with sophisticated/basic big data application identified in a peer-review survey. Internal assessments of the 16 organizations were obtained from 200 internal employees including top management (e.g. CEO), head of analytics, data scientists and other analysts. External assessments were obtained from 15 external consultants that have had consulting experience with the 16 organizations before. We also obtained other objective performance index, organizational profit growth, to cross-validate the analysis. Individual interviews and focus groups were also conducted to search for potential big data innovation issues, measures and industry expression.

Creating a pool of big data organizations

A peer-review survey was conducted at a big data related industrial event. The purpose of this survey was to create a pool of organizations with sophisticated/basic big data application, which allowed for the following internal assessments by organizational employees and external assessments by data analytics consultants. Seventy-seven industry people attended the events and were invited to the survey. Each person was asked to mention 5 organizations with sophisticated big data analytics and 5 organizations with basic big data analytics. We received 30 responses and in total 47 organizations were mentioned. The 47 organizations are from banking and financial services (13), retailing (10), computer software (7), online social networks (6), telecommunications (3), airlines (3), public sector (3) and mining and resources (2).

External assessment

Single-source dataset might be biased and can hardly provide a complete picture of the subject (Podsakoff et al. 2003; Reinartz, Krafft and Hoyer 2004). It is unsure to what extent the self-assessment by big data users is reliable. Thus, we obtained objective external assessment to ensure the validity of the analysis and to control common-method bias.

Seventy-eight external assessments were obtained from 15 data analytics consultants.

The 15 external judges have had analytics consulting projects with the organizations being assessed and thus have sufficient knowledge to conduct the assessments. Prior to the assessments, focus groups and in-depth interviews were conducted to achieve consistent evaluation criteria among all judges. External assessment was based on a paper-based questionnaire. Judges assessed the actual big data performance of the targeted organizations. To ensure the reliability and the consistency of external assessment, we asked the judges to provide us the description of the recent projects they conducted with the targeting organizations, and the reasons of their assessments. We only included those organizations with no less than 3 external judges, all of whom had consistent evaluations on the same companies. Seventeen organizations received consistent assessments from more than 3 judges and are included in our research.

Internal assessment

Table 4.1 ***Internal Assessment Samples Demographics (Study 3)***

Demographic variables	Frequency	Percentage
Gender		
Male	158	80.20%
Female	39	19.80%
Age		
18-25	21	10.71%
26-35	92	46.94%
36-45	59	30.10%
46-55	18	9.18%
56-65	6	3.06%
65+	0	0.00%
Hierarchy rank		
C-suite (CEO/CMO)	3	1.52%
Executive-level management	15	7.58%
High-level management (*e.g.* department manager)	21	10.61%
Mid-level management *(e.g.* coordinator)	33	16.67%
Lower-level management (*e.g.* executives)	42	21.21%
Senior employees	55	27.78%
Entry-level employees	29	14.65%
Years in the industry		
0-5 years	66	33.33%
6-10 years	77	38.89%
11-15 years	27	13.64%
16-20 years	15	7.58%
21-25 years	7	3.54%
26-30 years	5	2.53%
30+	1	0.51%

N = 200; frequency differences are due to missing data.

The internal assessment was conducted with the employees from the targeting organizations. Each internal assessment included a face-to-face interview and a paper-based questionnaire. The purpose of the interview was to examine the reliability of the answers in the questionnaires, to obtain reasons for the assessment and to identify other variables affecting organization analytics innovations. After the interview, a pretested questionnaire was given to each employee. Employees then assessed the strategic responsiveness, contextual factors and big data execution process of their organizations.

Two hundred employees from 16 organizations participated in our research and our response rate was 34 percent. The sample characteristics are shown in Table 4.1. Eighty percent were male and nearly half of the respondents were between 26 to 35 year old; more than 65 percent had over 5 year experience in current industries; and more than half of the respondents held management positions.

Measures

Questionnaires for internal and external assessments were developed based on previous research and interviews, and were both pre-tested and refined. Items of all variables are listed in Table 4.2. Both internal and external assessments were on a seven-point Likert scale from "-3" strongly disagree to "3" strongly agree.

Strategic responsiveness and organizational contexts. Items for strategic responsiveness were developed based on interviews; items for centralization were borrowed from Deshpande (1982); items for competitive intensity were borrowed from Moorman (1995).

Execution process. We measured two execution variables, which are evaluation and data-driven decision. The items for evaluation were adapted from Meyer and Goes' research (1988). Decision use of analytical results captured to what extent the insights from data are considered and used in the decision-making process. This variable and its measurement were adapted from Deshpande and Zaltman's research (1982) on the use of marketing research.

Big data performance. Big data performance measured to what extent the potential value of big data is achieved and has contributed to the organization performance. We proposed several object measures to capture organizational big data performance, such as data availability, infrastructure maturity, and analytics process. But all of these measures fail to provide a complete picture of big data performance. Thus, we decided to use the evaluation from external experts, who have sufficient knowledge of the targeted organizations, to measure big data performance. Items for the external assessment were developed based on the in-depth interviews with data analytics experts, and were pre-tested before external assessments.

Organizational normalized profit growth. To cross-validate our analysis, we obtained organizational normalized profit growth as the objective performance index. Concretely, organizational normalized profit growth was calculated based on the net profit before tax published in annual financial reports from the year big data projects were initiated to the year of 2014. The time of the initiation of big data projects was obtained from media reports. The use of normalized profit was to exclude the effects of unusual activities such as asset re-evaluation or write-off and to reflect the normalized operational performance. Results showed that the organizational normalized profit growth was significantly related to the actual big data performance evaluated by external judges ($p < .001$, correlation coefficient = .72).

Controlling and assessing common method biases

To minimize potential common method biases, data of independent and dependent variables were obtained from different sources (Podsakoff et al. 2003). Independent variables were from 200 employees from 16 organizations, whereas big data performance assessments were from 15 external consultants. Obtaining data from different sources avoid the presence of common rater biases.

Moreover, to assess and control the presence of common method biases in current research, we conducted two statistical remedies suggested by Podsakoff et al. (2003). The two remedies were Harman's single-factor test and the Single-method-factor approach. First, the exploratory factor analysis of the 26 items measuring strategic responsiveness, centralization, competition intensity, evaluation, data-driven decision and big data performance were loaded well on six different factors. That is, there is no one general factor can account for the majority of the covariance among measures. Second, following the Single-method-factor approach suggest by Podsakoff et al. (2003), we retested the model with all indicators loading on an unmeasured latent method variable. The inclusion of the latent method variable had little effects on both the measurement model and the structural model, with few changes in the significance and size of the path coefficients.

Results

The framework was examined with 200 individual-level observations from 16 organizations. We applied Multilevel Partial Least Squares (PLS) path modeling to test the framework. One reason is that it is suitable to analyze multiple relationships among blocks of variables (Sanchez 2013). Another benefit of PLS path modeling is its efficiency in establishing structural models even with a small sample size (Sarkar et al. 2001). The use of multilevel analysis was to account for the fact that the 200 individual-level observations were from 16 organizations. The analysis was conducted through the R package “plspm”.

Predicting the big data performance measured at organizational-level with explanatory variables measured by individuals, we adopted the latent variable multilevel model introduced by Croon and van Veldhoven (2007), which is suitable for analyzing data from micro-macro situation.

Measurement model

Twenty-six items were used to measure the 6 variables in both internal and external assessments, and profit growth was calculated through the normalised profits reported in the financial reports. Measurement model assessment is shown in Table 4.2 and 4.3.

Results of the measurement model indicated that of the 26 items, 24 had loadings larger than 0.8, and 2 items had loadings greater than 0.7 (Table 4.2). Of the 6 constructs, 3 constructs had Cronbach's Alpha greater than 0.9 and the rest were greater than 0.8. The statistics of the measurement model showed a high-level reliability of our measures.

Average variance extracted by each latent variable reflects the discriminant validity of measures (Fornell and Larcker 1981; Sarkar et al. 2001). A rule of thumb is to check for average variance extracted greater than 50% (Sanchez 2013). Results showed that of the 6 variables assessed through questionnaires, 5 had average variance extracted greater than 70% and the other one was greater than 60% (Table 4.3).

We also calculated the correlation to assess the criterion-related validity and discriminant validity (Table 4.3). Big data performance and profit growth were significantly correlated, consistent with previous theories (Davenport et al. 2001). Furthermore, some insignificant relationships (e.g. that between strategic responsiveness and centralization) among theoretical uncorrelated variables reinforce our assessment of discriminant validity.

Regarding the external assessment, the Krippendorff's alpha reliability coefficient of the 15 judges' assessments was 0.806, suggesting that the evaluation from the 15 external judges were consistent and reliable. In all, the outputs of measurement model showed that the reliability and validity of our measures are sufficient to support the following structural model analysis and interpretation.

Table 4.2 *Measurement Model: Cross-loadings of Items (Study 3)*

Items	Strategic responsiveness	Centralization	Competition intensity	Evaluation	Data-driven decision	Big data performance
In our strategic planning process, the person doing the planning changes our strategic direction according to the market trends.	**0.8251**	-0.2011	0.0444	0.2378	0.3747	NA
In the strategic planning process, we emphasize contingency plans.	**0.8374**	-0.1298	0.0728	0.3150	0.3770	NA
We adapt our strategy to customer and market trends.	**0.8513**	-0.1965	0.0916	0.3331	0.3751	NA
Our strategy changes as markets change.	**0.8377**	-0.0718	-0.0155	0.3103	0.3729	NA
If I wish to make my own decisions, I would be quickly discouraged.	-0.1087	**0.8115**	0.1488	-0.2488	-0.3096	NA
Even small matters of my job have to be referred to someone higher up for final answers.	-0.1778	**0.8916**	0.1359	-0.3332	-0.3559	NA
I have to ask my boss before I do almost anything.	-0.1764	**0.8895**	0.1340	-0.2360	-0.3352	NA
Any decision I make has to have my boss' approval.	-0.1422	**0.8715**	0.1653	-0.2411	-0.3128	NA
Competition in this product area is cut throat.	-0.0068	0.0680	**0.7847**	-0.0401	0.0890	NA
There are many promotion wars in this product area.	0.0297	0.1657	**0.8021**	-0.1414	0.0075	NA
Anything that one competitor can offer in this product area, others can match readily.	0.0071	0.2265	**0.7780**	-0.0971	0.0776	NA
Price competition is a hallmark in this area.	0.0087	0.1753	**0.8579**	-0.1854	0.0033	NA
One hears of a new competitive move in this product area almost every day.	0.0759	0.1231	**0.8324**	-0.0630	0.2020	NA
Our competitors in this product area are relatively weak. (R)	0.1353	0.0828	**0.8157**	-0.0898	0.1053	NA
The trial of big data was initiated before the decision to adopt.	0.3528	-0.2163	-0.0842	**0.8925**	0.3562	NA
Before deciding whether to use them, big data approaches were used in a small scale to see whether they could work.	0.2462	-0.3405	-0.1304	**0.9160**	0.4132	NA
We trialed big data so to evaluate its potential value to us before deciding whether to use it.	0.3400	-0.3189	-0.1230	**0.9477**	0.4781	NA
Big data was evaluated according to financial and/or strategic criteria before deciding whether to use it.	0.3678	-0.2310	-0.1278	**0.8703**	0.4037	NA
Without the insights from data, the decisions we have made would have been very different.	0.3468	-0.4095	0.1094	0.3582	**0.8822**	NA
The majority of the results from data analytics are used to support the decision-making.	0.4409	-0.3633	0.1289	0.4715	**0.9357**	NA
Few decisions would have been made without data analytics.	0.3633	-0.2416	0.0672	0.3441	**0.8065**	NA
The results of the data analytics have significant effects on the decision-making process.	0.4287	-0.3138	0.0411	0.4385	**0.9106**	NA
This organization has successfully extracted valuable insights from data.	NA	NA	NA	NA	NA	**0.9599**
This organization has already taken great advantage of data analytics.	NA	NA	NA	NA	NA	**0.9702**
The actual outcomes of using data analytics by this organization are significantly positive.	NA	NA	NA	NA	NA	**0.9501**
The value of data analytics is well achieved by this organization.	NA	NA	NA	NA	NA	**0.9753**

Note: N=200, except that the sample size for external assessment is 78; (R) suggests items were reverse-coded; NA= Not applicable.

Table 4.3 *Cronbach's Alpha, Average Variance Extracted and Correlation Matrix (Study 3)*

	Constructs	Cronbach's Alpha	1	2	3	4	5	6	7
1	Strategic responsiveness	0.8587	**0.72**						
2	Centralization	0.8899	-0.15	**0.75**					
3	Competition intensity	0.8975	0.12	0.12	**0.61**				
4	Evaluation	0.9280	0.42***	-0.27**	-0.04	**0.80**			
5	Data-driven decision	0.9072	0.46***	-0.30***	0.14	0.50***	**0.79**		
6	Big data performance	0.9800	0.21*	-0.12	-0.09	0.30***	0.37***	**0.93**	
7	Profit growth	N/A	0.11	-0.12	0.01	0.24*	0.27**	0.71***	**N/A**

Note: The diagonal (in bold type) shows the average variance extracted of the indicators.

* p < .05

** p < .001

*** p < .0001

Structural model

The product indicator approach was applied in the PLS path model to include the potential moderating effects (Sanchez 2013). A bootstrap validation with resamples was performed to validate the parameter estimates. A residual test was conducted to address the potential endogeneity issue (Germann, Ebbes and Grewal 2015). Results showed that the residuals of the big data performance model were not correlated with the independent variables, suggesting no unobserved variables might cause endogeneity issues. Results of the structural model are shown in Table 4.4, including the standardized coefficients of the direct, indirect and total effects among variables, and the R-square for each dependent variable. In the following part, we will present the direct effects, indirect effects and the effects of three significant interactions in the structural model.

Direct effects. The explained variance of the pre-evaluation was .25. Strategic responsiveness had a direct positive effect on the pre-evaluation of big data ($\beta = .58, p = .0000$). Hypothesis 4.3 was supported. Although centralization had insignificant direct effects on evaluation($\beta = .33, p = .2102$), it was included in the model because of the significant interaction with strategic responsiveness.

The R^2 of decision use of analytics results is .44. Strategic responsiveness had a direct effect on data-driven decision($\beta = .56, p = .000$). Hypothesis 4.4 was supported. Though with insignificant direct effects, centralization and competition intensity were included in the model because of the significant interactions between strategic responsiveness and centralization($\beta = -.56, p < .050$), and between centralization and competition intensity ($\beta = .52, p < .050$)

Table 4.4 ***PLS Path Model Results: Standardized PLS Coefficients of Direct and Indirect Effects (Study 3)***

Dependent variables	Independent variables	Hypotheses	Standardized coefficients			
			Direct	Indirect [a]	Mediators	Total [b]
Pre-evaluation [c]	Strategic responsiveness	4.3 (Supported)	.58***			
R^2= .25	Centralization		.33			
	Centralization × strategic responsiveness		-.60*			
Decision uses of analytics results [c]	Strategic responsiveness	4.4(Supported)	.56***			
R^2 = .44	Centralization		-.16			
	Competition intensity		-.07			
	Pre-evaluation		.27***			
	Centralization × strategic responsiveness	4.5(Supported)	-.56*			
	Competition intensity × Centralization	4.6(Supported)	.52*			
Big data Performance [d]	Pre-evaluation	4.1		.07	Decision uses of analytics results	0.7
R^2 = .55	Decision uses of analytics results	4.2(Supported)	.70*			
	Industry [e]		-.14			
	City [e]		-.39			

Note:
a Only significant indirect effects that meet the mediation conditions (Baron and Kenny, 1986) are shown in the table;
b Only significant direct and indirect effects are included in total effects;
c. Sample size in the models of evaluation and data-driven decision were 200.
d. The latent variable multilevel model (Croon and van Veldhoven 2007) was applied to predict the organization-level big data performance from the independent variables measured by individuals; sample size of organizational-level big data performance is 16; observations of each organization ranged from 6 to 33.
e. Industry and City were the control variables.
* $p < .05$
** $p < .001$
*** $p < .0001$

Given that the pre-evaluation and decision use of analytics results were measured by individuals, the latent variable multilevel method (Croon and van Veldhoven 2007) was applied to predict big data performance measured at organizational-level. The latent variable method is suitable when the dependent variable is from a higher level than the explanatory variables, namely the micro-macro situation (Croon and van Veldhoven 2007). In this model, 55 percent variance of big data performance was explained. Decision use of analytics results ($\beta = .70, p < .05$) had positive effects on big data performance, whereas the effect of the pre-evaluation on big data performance was not significant. Thus, Hypothesis 4.2 was supported, but Hypothesis 4.1 was not.

Indirect effects. Instead of having a direct effect, the pre-evaluation of big data analytics had an indirect effect on big data performance, mediating by the decision use of analytics results. Results showed the significant indirect effect, decision use of analytics results mediating the relationship between pre-evaluation of big data and big data performance ($\beta = .07$). This indirect effect met the mediation conditions in Baron and Kenny's research (1986), and passed the bootstrapping validation.

Interactions. Results revealed three significant interactions in the structural model (Table 4.4). To visualize the interactions, high-level of independent variables was determined as one standard deviation above the mean, and the low-level of independent variables was determined as one standard deviation below the mean. The value of y-axis reveals the correspondent scores of the dependent variables. Following Aiken and West's (1991) approach, we also examined the difference of the slopes to interpret the interactions.

Figure 4.1a illustrates effects of the interaction between strategic responsiveness and centralization on evaluation($\beta = -.60, p < .050$). The upward slope ($\beta = 1.18$) for low-level centralization suggests that when the organization is decentralized, the effect of strategic responsiveness on evaluation is stronger. The flat line ($\beta = -.01$) in Figure 4.1a shows that in centralized organizations, big data innovation would be evaluated regardless of

Figure 4.1a. Centralization affecting relation between strategic responsiveness and evaluation

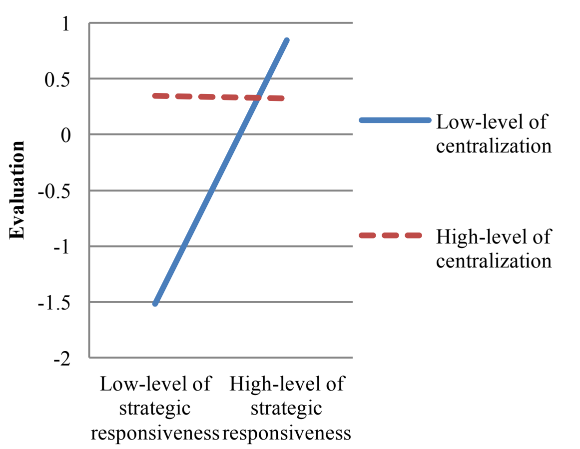
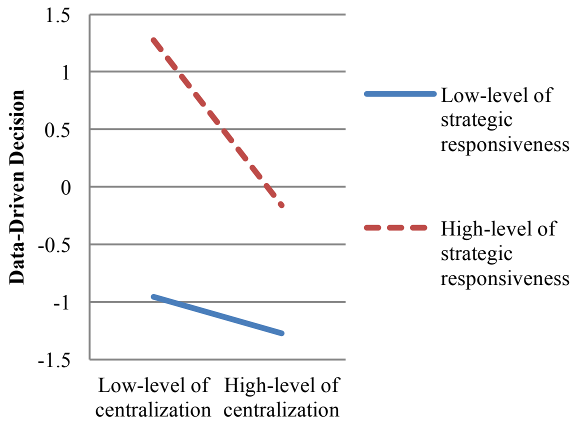


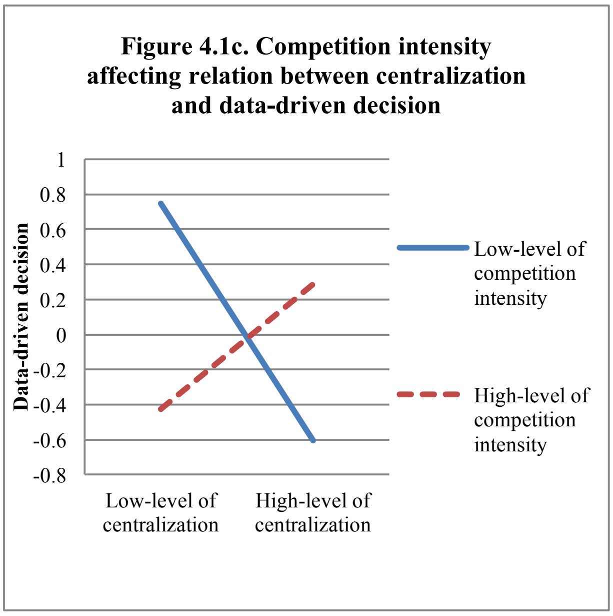
Figure 4.1b. Strategic responsiveness affecting relation between centralization and data-driven decision



management's strategic responsiveness.

Interaction between strategic responsiveness and centralization showed in Figure 4.1b also significantly affects data-driven decision($\beta = -.56, p < .05$). The slope of the high-strategic-responsiveness line is negative ($\beta = -.72$), whereas that of low-strategic-responsiveness line is almost flat ($\beta = -.16$). The interaction suggests that decentralization has stronger positive effects on the data-driven decision when organizations are highly strategic responsive. When management's strategic responsiveness is low, data-driven decision would be low regardless of organization centralization. Hypothesis 4.5 was supported.

Figure 4.1c shows that the increase of competition intensity alters the direction of the relationship between centralization and data-driven decision($\beta = .52, p < .05$). The slope of low competition intensity is -.68, whereas that of high competition intensity is .36. That is, centralization has a positive effect on data-driven decisions when the organization faces fierce competition, but has a negative effect when competition intensity is low. Hypothesis 4.6 was supported.



Discussion

Theoretical implications

Researchers have attempted to identify key success factors for big data performance. But the prior literature on big data performance mainly relies on fragmented qualitative analysis. There is scant theoretical framework with empirical test on data analytics performance. This study filled the void by developing a strategy-execution-performance framework based on a systematic literature review on decision science and analytics science. We examined the framework with pair datasets, which contains 200 samples from 16 organizations and 78 samples from 15 external consultants. Results significantly supported the strategy-execution-performance framework. On one hand, big data performance has 55 percent of variance explained by big data execution process, which includes a thorough evaluation of big data and the data-driven decision. On the other hand, the two execution process variables are significantly affected by strategic responsiveness, centralization and competition intensity.

Our research fills the void of data analytics performance by building and testing the strategy-execution-performance framework to predict big data performance. Researchers and practitioners have put extensive efforts into data analytics, such as scanner data analytics, clickstreams analytics and big data analytics (Barton and Court 2012; Bucklin and Gupta 1999; Davenport et al. 2001; McAfee and Brynjolfsson 2012). However, there is hardly any established model explaining how organizations achieve a high-level of data analytics performance. Bucklin and Gupta (1999) provided a comprehensive comparison between the use of scanner data analytics by researchers and practitioners, and suggested how researchers can accelerate the diffusion of scanner data analytics to practitioners. This research (Bucklin and Gupta 1999), however, did not take a step further towards how practitioners can turn scanner data into valuable results. Furthermore, research on big data analytics have demonstrated the tremendous potential of big data, and pointed out some important capabilities and resources to succeed in big data analytics (Brown et al. 2011; Bughin et al. 2011). But these studies are rather fragmented and inconclusive, without systematic theoretical and empirical analysis. The most relevant data analytics research is from Davernport et al. (2001). Based on the field study with over 100 firms, Davenport et al. (2001) discovered a range of primary success factors of data analytics, with which a *data to knowledge to results* framework was built. But few studies have quantitatively examined the predictive power of this framework. Filling the gap, we took a step toward a theoretical framework of data analytics performance and collected data from 16 organizations to test the framework. Our findings pinpoint the important roles of strategy responsiveness, execution process and organizational contexts to big data performance.

This study shows the importance of strategic responsiveness in data analytics activities. Strategic responsiveness is an organizational capability, with which organizations are able to proactively adapt its strategy to the changing environment and maintain a right strategic direction. In the big data context, organizations with high-level strategic responsiveness are more likely to carefully evaluate big data before the adoption and apply analytics results to make decisions. However, the positive effects of strategic responsiveness are weaker in centralized organizations. In centralized organizations, the data-driven decision is more often used when decision makers perceive a high-level of competition.

Big data performance has 55 percent variance explained by the execution process variables, namely evaluation and data-driven decisions. On one hand, a thorough evaluation makes sure that there is a potential of using big data. On the other hand, data-driven decisions, reflecting the quality, actionability and political acceptability of data inputs, improve the value of decision outputs and thus have a positive influence on performance.

Our research also contributes to decision science literature. According to decision science literature, a rational decision process positively affects organizational performance (Priem et al. 1995). This research provides a deeper and richer portrait of rational decision process. To make rational decisions, organizations should have an evaluation process prior to the decision process. The evaluation of both external and internal factors guarantees the quality of inputs in the decisions. The following data-driven decision process then turns the high-quality inputs from the evaluation process into rational decision outputs, which have significantly positive effects on performance. Moreover, our findings suggest that the rational decision process is highly contingent on organizational contexts, especially organizational capabilities in proactively adapting its strategy to the changing environment.

Managerial implications

When it comes to the revolutionary innovation, managerial fads and fashions come together (Abrahamson 1991). Executives might spend millions of dollars without achieving expected returns. We have seen executives' fads into scanner data, customer relationship management system and various other analytics innovations (Davenport et al. 2001), but very few organizations have succeeded in turning data into valuable results. All of the 16 organizations in our research have an enterprise-wide data analytics platform and are spending millions of dollars into the analytics infrastructure, technologies and tools, and talents. But the data analytics performance varies dramatically. The varying performance has indicated that monetary investments cannot guarantee positive performance.

Our findings direct the academic and empirical attention to the importance of organizational strategic responsiveness and execution process for big data success. Being strategic responsive, organizations can quickly react to environmental changes and maintain a right strategic direction. With the right strategy, executives can frame the right questions to solve business challenges, allocate analytical resources and manage the analytics appropriately. Moreover, the importance of big data execution process is not only significant in our statistical test but also identifiable in practice. To carry out data-driven decisions requires the efforts from both decision makers and data analysts. Decision makers should appreciate the value of analytical insights even if these insights do not meet their expectations. Data analysts should offer decision makers insights that are of high value and actionability. These efforts improve the quality of decision inputs and guarantee the decision outputs, ultimately contributing to the overall big data performance. Significantly, organizations would benefit to a great extent from greater attention toward improving both their strategic responsiveness and rationalizing their execution process.

In the big data context, the role of centralization is somehow paradoxical. On one hand, centralized organizations tend to conduct a thorough pre-evaluation of big data regardless of the strategic responsiveness. That is, centralization is a highly supportive context for the big data pre-evaluation, a critical process of a rational adoption decision. On the other hand, analytical insights receive few attentions in centralized organizations, even if they are highly responsive to the changing environment. In other words, centralization weakens the positive effect of strategic responsiveness on the use of analytical results. This can be explained by the information distortion and blockage effects of centralization (Deshpande 1982). Centralization is apparently playing a cheerless role when it comes to the decision use of analytics results.

However, the suppressing effect of centralization during the decision-making process flips over when the extern competition is high. When facing intense external competitions, more centralized organizations tend to have more usage of analytics results. That is to say, one should pay attention to the insufficient use of analytics results in centralized organizations, which face relatively low levels of competition, as the insufficient use of analytics results might be the reason of big data performance below expectations. If this is the case, organizations should establish particular procures for preventing information distortion and blockage during the information sharing process.

Limitations and further research

There are noteworthy limitations, which suggest opportunities for future investigations. First, we used external consultant assessments to measure big data performance, which might be biased. We conducted focus groups and interviews with big data users and consultants to search for reliable measures of big data performance. Compared to other measures such as infrastructure maturity and analytics process, expert scores are more sophisticated and appropriate. To minimize the possibility of potential biases, we selected only experts with sufficient consulting experience with the targeted firms, and selected only firms with no less than three external assessments. Krippendorff's alpha reliability coefficient suggested an acceptable level of inter-rater reliability. Future research can search for more objective and reliable measures for data analytics performance.

Second, as the study is based on data from the perceptions of big data users and consultants in one country (Australia), we might consider potential problems when generalizing the findings. To control and assess the presence of common method biases, we obtained data of independent and dependent variables from two sources, and conducted two statistical remedies suggested by Podsakoff et al. (2003). Both of the Harman's single-factor test and the Single-method-factor approach suggested a very low-level common method bias present in current study. Besides, dependence on the data of big data analytics might weaken the generalization of the findings to other types of data analytics. Although our strategy-execution-performance framework is largely consistent with major arguments in data analytics research (Daverport et al. 2001), we should acknowledge that our findings might not be entirely applicable to explain all types of data analytics activities. Future research can investigate the strategy-execution-performance path in multiple-analytics context and assess its power to explain the data analytics performance in general. In this vein, an appealing question is whether organizational strategic responsiveness and analytics execution process account for organizational data analytics performance in a general sense.

Thirdly, the explanatory variables of this research were from the commonly mentioned variables by both practitioners and researchers. These variables were mostly at the organizational level. The underlying assumption was that organizational analytics performance was endogenous to organizational contexts. However, the confounding effects of extraneous variables might threaten the validity of these proposed relationships between firm contexts and analytics performance. To reduce omitted variables bias, we included two control variables in our model, i.e. industry and city, which allowed us to come closer to the predictive power of the strategic-execution-performance framework. The residuals test showed that the residuals of big data performance model were not correlated the independent variables, indicating a small chance of endogeneity issue. For future investigations, researchers may include variables from industrial or higher levels when addressing analytics performance.

In conclusion, this study addresses a heated but fundamental question in data analytics: How organizations can achieve masterful big data performance? By establishing and testing the strategy-execution-performance framework with data from both 200 big data users and 15 big data consultants, this study suggests that the answer to a large extent resides in organizational capability in proactively adapting the strategy to environment dynamics, and big data execution process. Deficiencies in either big data strategy or execution will lead to disastrous loss in big data activities.

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CHAPTER 5: CONCLUSIONS AND DISCUSSION

Big data has become a new source of competitive advantage (Manyika et al. 2011). Increasingly more organizations have invested massively in big data innovation to achieve new competitive growth (e.g. Brown, Chui and Manyika 2011; Eyers 2014; Head 2013; Ramli 2013). The purpose of this thesis was to examine the effects of organizational contexts, big data attributes and social capital on individual acceptance of big data, as well as the effects of organizational contexts and decision process on big data performance at the organizational level. Face-to-face interviews and structured questionnaires were used to collected data from the low-to-high level of managers, junior and senior data analysts, and other data-relevant employees from data-intensive organizations. The research questions, theoretical framework, data collection process and analysis, as well as results of the three studies were presented in Chapter 2 to 4, respectively. Conclusions of the thesis and discussion are presented in this chapter.

Chapter 5 starts with a summary of findings from the three studies, including statistical findings, interpretations and inferences, as well as the comparison with findings in the prior literature. Theoretical and managerial implications, limitations and recommendations for future studies will be presented subsequently. Finally, a summary of this chapter will be highlighted.

Summary of Findings

Findings of each study are summarized to resolve the research questions raised in this research. The summary mainly focuses on the interpretations and inferences of the statistical findings. Related findings in prior literature will be discussed as well.

Findings of Study 1

The research question of Study 1 was how big data attributes and organizational contexts interact and affect individuals' acceptance of big data. Study 1 developed six hypotheses proposing the effects of interactions between organizational contextual factors and big data attributes. The results, presented in Chapter 2, showed that six interactions between contextual factors and big data attributes have significant influences on individuals' intentions to adopt big data.

Organizational politics and information seeking (i.e. compatibility). Hypothesis 2.1 in Study 1 proposed how the interaction between organizational politics and information seeking (i.e. compatibility) affects individuals' intentions to adopt big data during the pre-adoption period. This hypothesis was supported as a significant interaction was found between organization politics and information seeking during the pre-adoption period. The results indicated that the presence of organizational politics suppressed the positive effect of information seeking (i.e. compatibility) on the intentions to adopt big data during the pre-adoption period. That is, information seeking (i.e. compatibility) has a positive effect on individuals' intentions to adoption big data in the low-political context; but the positive effect diminishes in the high-political context. The result in low-political context confirmed Rogers' innovation diffusion theory, which suggested the higher the perceived compatibility, the more likely to adopt innovation. The effect of information seeking (i.e. compatibility) in low-political context confirmed previous findings in individual acceptance of information technology literature (e.g. Plouffe, Hulland and Vandenbosch 2001). When individuals are actively seeking information, perceiving high compatibility of big data with current work, they would be more likely to adopt big data. This positive effect of information seeking was supported when organizational politics is low.

When organizational politics is high, the positive effect of information seeking (i.e. compatibility) on individuals' intentions to adopt big data diminishes. That is, high-level of political games suppress the positive effects of compatibility on individuals' intentions to adopt big data. The results were consistent with Sasser and Koslow's finding (2012) that organization politics weakens the positive effect of expertise on creativity. Politics are resulted from deliberate behaviors with attempts to achieve self-interests, which often conflicts with others' interests (Eisenhardt and Bourgeois 1988). Political game players intentionally command resource allocation, manipulate the situation and control the decision-making process (Sasser and Koslow 2012). To politics players, being data-driven means giving away the power of decision manipulation. Being data-driven is a source of organizational competitive advantage, but not a source of individual competitive advantage for politics players. This explains why the presence of political games inhibits the effect of compatibility on individuals' intentions to adopt big data.

Organizational politics and trialability. Hypothesis 2.2 proposed that organizational politics decreases the positive effects of trialability on individuals' intentions to adopt big data during the pre-adoption period. Results supported the hypothesis and showed that the positive effect of trialability is stronger when the organizational politics is low. The relationship between trialability and the intention to adopt big data in non-political organization supported Rogers' innovation diffusion theory (1995). However, when political games are played, the effects of trialability diminishes. Trying out big data, individuals get more insights of the application and potential outcomes of big data. The more individuals understand big data, the more they know big data is not compatible with politicians. When using big data brings potential conflicts with game players, individuals tend not the adopt it.

Organizational politics and relative advantage. Hypothesis 2.3 proposed that organizational politics enlarges the positive effects of relative advantage on individuals' intentions to adopt big data during the pre-adoption period. Results supported this hypothesis and showed that the positive effect of relative advantage was stronger in highly political context. The results confirmed Rogers' innovation diffusion theory (1995) that the higher relative advantage perceived, the more likelihood to adopt innovation. The results supported previous findings in individual acceptance of information technology literature where relative advantage has consistently positive effects on individuals' intentions to adopt new technology (e.g. Agarwal and Prasad, 1997; Karahanna, Straub and Chervany, 1999; Plouffe et al. 2001; Venkatesh, et al. 2003). When marketers recognize that big data has higher level of relative advantage, such as economic returns, low costs, social prestige, and the saving in time and/or effort, and so forth (Rogers 1995), they are more willing to adopt big data.

The existence of organizational politics enlarges the positive effect of perceived relative advantage on individuals' intentions to adopt big data. Game players use politics to control resource allocation and manipulate decisions to achieve self-interests (Eisenhardt and Bourgeois 1988; Sasser and Koslow 2012). The power exercise might lead to strong feelings of unfairness, disenfranchisement and disappointment (Sasser and Koslow 2012). Data analytics is an effective weapon to fight against politics. The objective truth from data makes it difficult for game players to subjectively manipulate decisions. In a highly political context, the effects of relative advantage on individuals' intentions to adopt big data are strengthened.

Centralization and relative advantage. Hypothesis 2.4 proposed how centralization and relative advantage interact and affect individuals' intentions to adopt big data during the pre-adoption period, and the results supported this hypothesis. The results showed that the interaction between centralization and relative advantage had a significant effect on individuals' intentions to adopt big data. Concretely, the positive effect of relative advantage is stronger in decentralized organizations than in centralized ones. The positive correlation between relative advantage and individuals' intentions to adopt big data in decentralized organizations confirmed Rogers' innovation diffusion theory (1995) and previous findings in individual acceptance of information technology (e.g. Agarwal and Prasad, 1997; Karahanna, Straub and Chervany, 1999; Plouffe et al. 2001; Venkatesh, et al. 2003).

The line of high-centralization line was consistent with that in the use of market research literature (e.g. Deshpande 1982; Deshpande and Zaltman 1982). Studies on the use of market research found that centralization had a significantly negative effect on manager's use of marketer research (e.g. Deshpande 1982; Deshpande and Zaltman 1982). The main explanation was that managers with more participation in the decision process would perceive more responsibilities and thus seek more research support to make decisions.

Centralization and information seeking (i.e. compatibility). The interaction between centralization and information seeking (i.e. compatibility) during the pre-adoption period was examined with hypothesis 2.5, and the results supported this hypothesis. The results demonstrated that the interaction between centralization and information seeking (i.e. compatibility) had significant effects on individuals' intentions to adopt big data. Specifically, the positive effect of information seeking (i.e. compatibility) on individuals' intention to adopt big data is much stronger in the centralized context than that in the decentralized context. The positive effect of information seeking (i.e. compatibility) confirmed Rogers' innovation diffusion theory (1995) that the more compatibility one perceives, the high likelihood of adoption. One's information seeking reflects his/her perceived compatibility of new data and information. In the centralized context, the perceived compatibility of big data increases, because of the enterprise-wide benefits of big data. From this perspective, centralization is a favorable contextual factor that enlarges the positive correlation between information seeking (i.e. compatibility) and individuals' intention to adopt big data during the pre-adoption period.

Hypothesis 2.6 proposed how centralization and trialability interact and affect intentions to adopt big data during the pore-adoption period, and the findings supported this hypothesis. The findings indicated that centralization increased the positive effect of trialability on individuals' intentions to adopt big data during the pre-adoption period. In the decentralized context, trialability has a weak effect on intentions to adopt big data, whereas in the centralized context, this positive effect is increased significantly.

Study 1 examined how organizational contextual factors and big data attributes interact and affect individual acceptance of big data. The results showed that six interactions (i.e. organizational politics and information seeking, organizational politics and relative advantage, organizational politics and trialability, centralization and information seeking, centralization and trialability, and centralization and relative advantage) had significant influences on individuals' intentions to adopt big data during the pre-adoption period; and no interactions had significant influences on the actual usage of big data. Across these findings, organizational contextual factors' effects were more significant during the pre-adoption period than the post-adoption period.

Findings of Study 2

Given the prevalence of the partnership with consulting firms to exploit big data, the purpose of Study 2 was to examine how consulting assets affect individual acceptance of big data during three stages (i.e. adoption, diffusion and implementation). Five hypotheses were used to examine the effects of consulting assets on individuals' intention to adopt big data during the adoption stage, intention to use big data during the diffusion stage and the actual usage of big data during the implementation stage, respectively. The results presented in Chapter 3 demonstrated that the effect of consulting assets on individuals' intentions to adopt big data during the adoption stage was not significant, that on individuals' intentions to use big data during the diffusion stage was moderated by big data attributes, and that on the actual usage of big data during the implementation was significantly positive.

Consulting assets and big data adoption. The results showed that consulting assets had insignificant correlation with individuals' intention to adopt big data at the adoption stage. That is, consulting assets had no significant motivating effect on the individual acceptance of big data. The results confirmed previous findings from individual acceptance of information technology literature, which showed that social influence was not significantly correlated with individuals' intention to adopt information technology (e.g. Venkatesh et al. 2003). The results were also consistent with our interview findings. According to our interviews, consulting firms were usually hired after the adoption decision had been made. This means that consulting firms have little participation in the adoption decision process and thus few influences on individuals' intention to adoption.

The insignificant effects of consulting assets at the adoption stage can be explained with Nahapiet and Ghoshal's (1998) four conditions, without which social capital is not effective. The four conditions are opportunity, motivation, value expectancy and capability. The connections to consulting firms provide opportunities for resource (e.g. knowledge) exchanges. Despite the opportunities for resource exchanges with consulting firms, the motivations and value expectancy of potential adopters are highly uncertain. These two uncertain conditions lead to the insignificant effects of consulting assets on individuals' intentions to adopt big data.

Consulting assets and big data diffusion. Four hypotheses were developed to examine how consulting assets and big data attributes interact and affect individuals' intention to use big data at the diffusion stage. Two hypotheses were supported and the unexpected interaction between consulting assets and information seeking was found significant.

Hypothesis 3.1 proposed how the interaction between consulting assets and relative advantage affect individuals' intentions to use big data at the diffusion stage, and the results supported this hypothesis. The results indicated that the interaction between consulting assets and relative advantage had significant effects on individuals' intention to use big data. When individuals perceive a high-level of relative advantage, consulting assets are positively related to individuals' intentions to use big data. When individuals perceive a low-level of relative advantage, consulting assets have negative effects on intention to use big data. The results supported the Nahapiet and Ghoshal's (1998) value expectancy view that actors in the networks must expect the interactions and resource exchanges in the networks can create value. The value expectancy is one condition for social capital to be effective (Nahapiet and Ghoshal 1998). The perceived relative advantage reflects individuals' expectation for the potential benefits of big data. When the perceived relative advantage is high, individuals are more willing to interact and exchange knowledge with big data consultants. The information and knowledge from big data consultants reinforces the potential of big data, increasing individuals' intentions to use big data. By contrast, when the perceived relative advantage is low, information and knowledge from consultants reinforces the disadvantages, decreasing individuals' intentions to use big data.

Hypothesis 3.2 proposed how the consulting assets and ease of use interact and affect individuals' intentions to use big data at the diffusion stage, and the results supported this hypothesis. The results demonstrated that the interaction between consulting assets and ease of use had significant effects on intention to use big data. When big data is perceived as difficult to use, consulting assets could increase individuals' intentions to use big data. But when big data is perceived as easy to use, individuals have high intentions to use big data regardless of consulting assets. The results confirmed Rogers' innovation diffusion theory (1995) that complexity is negatively correlated with innovation adoption. Consulting assets have weaker effects when big data is perceived as easy to use. By contrast, consulting assets have strong positive effects on individuals' intention to use big data when big data is perceived as difficult to use. The reason is that interactions with consultants enable the exchanges of know-how and know-what knowledge (Nahapiet and Ghoshal 1998), making it easier to use big data.

Because of the compound nature of big data, the observability construct did not pass the factor analysis and was dropped. Hypothesis 3.3 on the interaction between consulting assets and observability was not supported. The interaction between trialability and consulting assets was not significant and hypothesis 3.4 was not supported.

The interaction between consulting assets and information seeking had significant effects on individuals' intentions to use big data at the diffusion stage. When individuals are open to and actively seeking new information, consulting assets have negative effects on their intentions to use big data. One possible reason may be the interactions with consultants, together with the information flows from the interactions, slow down or even disrupt the decision-making process, decreasing one's intention to use big data. By contrast, consulting assets have positive effects on those who are not open to and actively seeking new information.

Consulting assets and the implementation stage. The relationship between consulting assets and the actual usage of big data at the implementation stage was examined with Hypothesis 3.5. The results showed a significantly positive relationship between consulting assets and the actual usage of big data, supporting Hypothesis 3.5. The results demonstrated that the more consulting assets one have, the more he/she uses big data at the implementation stage. At the implementation stage, the three conditions (opportunity, value expectancy and motivation) from Nahapiet and Ghoshal's (1998) study have been met. The rest condition, capability, can be improved by the know-how and know-what knowledge (Landry et al. 2002; Tsai and Ghoshal 1998) flows from consulting firms. That is, consulting assets can be transformed into individuals' capabilities, assisting the use of big data. The results confirmed social capital theory and previous findings in social capital literature (e.g. Landry et al. 2002; Nahapiet and Ghoshal's 1998; Tsai and Ghoshal 1998).

Study 2 examined how the social capital derived from relationships with consulting firms affect individual acceptance of big data at three stages (i.e. adoption, diffusion and implementation). The results demonstrated that consulting assets had no significant effects on intention to adopt big data at the adoption stage; that the effects of consulting assets on intention to use big data at the diffusion stage were moderated by big data attributes; and that consulting assets had directly positive effects on the actual usage of big data at the implementation stage. Simply put, consulting assets have diffusing and facilitating, rather than motivating effects, on individual acceptance of big data.

Findings of Study 3

The research purpose of Study 3 was to examine factors underpinning big data performance at the organizational level. A strategy-execution-performance framework was developed based on literature review. Six hypotheses were used to test this framework. The results presented in Chapter 4 showed that big data performance at the organizational level was significantly correlated with the execution process variables (i.e. the pre-evaluation and decision uses of analytics results), and execution process variables were significantly affected by strategic responsiveness and organizational contextual factors (i.e. centralization and competition intensity).

Execution process and big data performance. The results showed the significant relationships between decision process variables (i.e. evaluation and data-driven decision) and big data performance at the organizational level. Specifically, both of the evaluation of big data and the data-driven decisions had positive effects on big data performance at the organizational level.

The correlation between the evaluation of big data and big data performance at organization was tested with Hypothesis 4.1, and the results showed that the pre-evaluation of big data had significantly indirect effects on big data performance. The results indicated that the more evaluation of big data, the better big data performance is. A thorough evaluation of big data decreases the risks of managerial fads and fashions. Managerial fads and fashions exist because organizations sometimes adopt potentially inefficient innovations or reject potentially efficient innovations (Abrahamson 1991). Without a thorough evaluation of the potential outcomes of big data, organizations are exposed to the risk of adopting potentially inefficient innovation. By contrast, through a thorough evaluation of big data, managers gain insights into the compatibility, potential outcomes and complexity of big data, which educates individuals about big data application and supports a rational adoption decision process. A rational adoption decision based on a thorough evaluation, which minimizes the risk of adopting inefficient innovation, is positively related to big data performance at the organizational level.

Hypothesis 4.2 tested the correlation between decision-uses of analytics results and big data performance at the organizational level, and the results supported this hypothesis. The results indicated that the more data-driven decisions, the better big data performance is. The results supported one major suggestion in data analytics studies that data-driven decisions yield better results (e.g. Davenport et al. 2001; McAfee and Brynjolfsson 2012). On one hand, when decisions are not based on data but other factors such as political acceptability, weak rationality threatens the decision outcomes (Deshpande and Zaltman 1982; Priem et al. 1995; Weiss 1977 & 1980). On the other hand, the use of data analytics to support decision process reflects the quality and actionability of the analytical results, which in turn guarantees the decision outcomes (Deshpande and Zaltman 1982; Weiss 1977 & 1980).

Strategic responsiveness and analytics execution process. The results showed that execution process variables (i.e. evaluation and data-driven decision) were significantly correlated with strategic responsiveness and its interactions with organizational contextual factors (i.e. centralization and competition intensity). Concretely, the evaluation of big data was positively correlated with strategic responsiveness. The interaction between centralization and strategic responsiveness also had significant effects on the evaluation of big data. Data-driven decision was correlated with strategic responsiveness, evaluation, and two interactions (i.e. between strategic responsiveness and centralization, and between competition intensity and centralization).

Hypothesis 4.3 in Study 3 proposed that strategic responsiveness is positively correlated with big data evaluation, and the results supported this hypothesis. The results indicated that more strategic responsive organizations are more likely to thoroughly evaluate big data before the adoption. The results supported the major assertion in data analytics studies that the right strategy is a prerequisite to exploit big data and achieve valuable results (e.g. Barton and Court 2012; Brown et al. 2011; Davenport 2006; Davenport et al. 2001; McAfee and Brynjolfsson 2012). Being strategic responsive, organizations are actively matching internal resources and capabilities with external environment. A strategic responsive organization is more likely to evaluate the potential of big data, and adapt internal resources and capabilities to achieve big data potential.

Interview findings of present research supported the positive relationship between strategic responsiveness and the evaluation of big data. Being in a volatile industry, one leading Australian retailer watches closely at market trends and competitors' moves, because every change in the competition dynamics can be fatal. When its major competitor initiated a loyalty programme by collecting customer data and identifying patterns to achieve competitive differentiation, this retailer allied with a big data consulting firm in the following year with attempts to understand the value of big data, as well as how to adopt and implement big data innovations. Experts from the consulting partner were brought into the retailing organization and worked closely with different teams to evaluate the potential of big data and to provide user cases for its decisions. By contrast, a telecommunication organization, which was less proactive in adapting strategy, missed the critical timing of exploiting big data to handle the decreasing customer satisfaction and the increasing churn. The telecom was following a profit-driven strategy and experiencing an increasing churn. Voices had come from the bottom, suggesting that customers should be taken better care of. But the strategy had not been adapted until the new chief executive officer came. Piles of data were sitting in this telecom not exploited until the initiation of a customer-oriented strategy by the new chief executive officer. These two cases well illustrated that the more strategic responsive an organization is, the more likelihood it would thoroughly evaluate big data.

The effect of strategic responsiveness on data-driven decision was tested with Hypothesis 4.4 in Study 3. The results supported Hypothesis 4.4, showing that strategic responsiveness was positively correlated with data-driven decisions. The results supported previous qualitative findings by Davenport et al. (2006), which suggested that managers with strategic vision are more likely to value data analytics. Managers with strategic vision actively consider strategic questions: What are our core competences? How do current customers like us? Why do customers churn? How to target potential customers? Answering these questions requires insights from data, such as customer transactional data and social media data. The more strategic responsive the organization, the clearer what data it requires (Davenport et al. 2001).

The case of Harrah's Entertainment (Davenport et al. 2001) exemplified the correlation between strategic responsiveness and data-driven decisions. Harrah's managers were able to promptly react to the stop of the sudden great increase in legalized gaming jurisdictions. To react to the new trend, Harrah's managers adapted the strategy and decided to focus on existing casinos and the cross-sell of its 18 properties. To support the new strategy, massive data were analyzed to understand customers and identify gambling patterns. This case well exemplifies the correlation between being strategic responsive and the use of data to support decisions.

Hypothesis 4.5 proposed that centralization weakens the positive correlation between strategic responsiveness and data-driven decision, and the results supported the hypothesis. The results indicated that in decentralized context, strategic responsiveness had a strong and positive effect on data-driven decision, whereas in centralized context, strategic responsiveness had a weaker positive effect on data-driven decision. This finding can be explained by the information distortion and blockage effect mentioned by Deshpande (1982). Deshpande (1982) suggested that information is likely to be distorted or blocked when it is passed from one hierarchical level to another in centralized organizations. Distortion is resulted from individual differential selective perception. Blockage is due to individuals' intentions to present only the information expected by their superiors. Given the presence of information distortion and blockage in centralized context, strategic responsive decision-makers might have less data to support the decision process than in decentralized context. From this perspective, decentralization is a more favorable contextual factor enhancing the positive correlation between strategic responsiveness and data-driven decision.

The results also showed that the interaction between centralization and strategic responsiveness significantly affected the evaluation of big data. Concretely, strategic responsiveness had a stronger positive effect on the evaluation of big data in the decentralized context, whereas in centralized context, organizations are willing to evaluate big data regardless of is strategic responsiveness. The positive correlation between strategic responsiveness and evaluation in decentralized context supported data analytics researchers' emphasis on organizational strategy as a critical prerequisite of data analytics (e.g. Barton and Court 2012; Brown et al. 2011; Davenport 2006; Davenport et al. 2001; McAfee and Brynjolfsson 2012). Organizational willingness to evaluate big data in centralized context reflects the suitability of big data platform for enterprise-wide uses and centralized decisions.

The interaction between competition intensity and centralization was examined with Hypothesis 4.6. The results supported this hypothesis. The interaction between competition intensity and centralization was found to have significant effects on data-driven decisions. When organizations face highly intense competition, power consolidation increases data-driven decisions. By contrast, when organizations are lack of competition, power centralization weakens data-driven decisions.

Study 3 developed and tested the strategy-execution-performance framework to explain big data performance at the organizational level. The results showed that the more evaluation of big data and data-driven decisions, the better organizational big data performance is. The results also supported the significant effects of strategic responsiveness and organizational contextual factors (i.e. centralization and competition intensity) on big data execution process. Both of the evaluation and data-driven process are positively correlated with strategic responsiveness. In centralized context, organizations are willing to evaluate big data regardless of strategic responsiveness. The correlation between strategic responsiveness and data-driven decisions is weaker in centralized context than in decentralized one. When organizations are facing highly intense competition, centralization increases data-driven decisions. When the competition is weak, centralization weakens data-driven decisions.

Theoretical Implications

This research aimed to explain individual acceptance of big data and organizational big data performance. In Study 1, Rogers' (1995) innovation diffusion theory and situational theory (e.g. Adkins and Naumann 2001; Meyer et al. 2010) were integrated to explain individual acceptance of big data. This study has not only confirmed the predictive power of Rogers' (1995) innovation diffusion theory, but also extended the relationships between innovations attributes and adoptions to a broader context through the use of situational theory. Study 2 applied social capital theory to explain the effects of consulting firms on three big data innovation process, and found that consulting assets significantly affect the diffusion and implementation stages instead of the adoption stage, providing a more comprehensive picture of the variant effects of social capital in innovation process. Study 3 developed and tested the strategy-execution-performance framework to explain big data performance at the organizational level. Building on top of previous qualitative studies on data analytics, Study 3 has pioneered the use of quantitative approach to build and test a strategy-execution-performance framework to explain and predict data analytics performance.

The theoretical implications are discussed in this section. This is more of an integrative discussion of the research findings and the theoretical implications. The emphasis is on how these research findings have contributed to previous theories and empirical findings.

Innovation diffusion theory and situational theory

The research has confirmed the power of innovation diffusion theory (Rogers 1995) in explaining individual acceptance of information technology. The results demonstrated the significant effects of big data attributes on individual acceptance of big data. Additionally, the results indicated that the relationships between big data attributes and individual acceptance of big data were contingent on organizational contexts, highlighting the need to consider contextual factors for future theory development.

Predictive power of innovation attributes. Results presented in Chapter 2 and 3 showed the significant effects of big data attributes on individual acceptance of big data, confirming the predictive power of Rogers' (1995) innovation diffusion theory. The results indicated that relative advantage of big data had significant effects on individuals' intention to adopt and use big data, which were consistent with Rogers's view that the more relative advantage perceived, the more likely one adopt the innovations. The strong effects of relative advantage were also consistent with empirical findings, which have demonstrated a strong and consistent relationship between relative advantage and individual acceptance of technology (e.g. Agarwal and Prasad, 1997; Karahanna et al. 1999; Plouffe et al. 2001; Venkatesh, et al. 2003). The consistent effects of relative advantage from existing studies and current research have implied and reinforced the wide applicability of relative advantage-adoption relationship to explain individual acceptance of information technology.

Complexity (i.e. the reversal of ease of use), compatibility (i.e. information seeking), trialability and observability are the other four attributes in Rogers' (1995) innovation diffusion theory. The effects of these four attributes on individual acceptance of information technology have been somehow inconsistent across empirical studies. For example, Plouffe, et al. (2001) found that compatibility, visibility and trialability had significant effects on intention to adopt, whereas Venkatesh et al. (2003) found that intention to adopt was significantly correlated with ease of use, rather than compatibility, trialability and visibility. The present research found that trialability and information seeking (i.e. compatibility) had significant effects on intention to adopt big data and that ease of use had significant effects on intention to use big data, partly consistent with previous empirical findings. The inconsistent effects of complexity (i.e. the reversal of ease of use), compatibility (i.e. information seeking), trialability and observability showed in previous and present research may due to the nature of the information technology under studied, organizational contexts, or other different settings

(Venkatesh, et al. 2003). These inconsistencies imply that the predictive power of complexity (i.e. the reversal of ease of use), compatibility (i.e. information seeking), trialability and observability from Rogers' (1995) innovation diffusion theory might vary across different settings and should not be over generalized without consideration of the research contexts.

Effects of contextual factors. The current research extended the theoretical framework of individual acceptance of information technology by including contextual factors, and illustrating the effects of cross-level interactions between big data attributes and contextual factors. Previous research has examined the moderating effects of organizations settings, such as voluntariness in the study of Venkatesh, et al. (2003). Going a step further, this research examined the effects of two contextual factors (i.e. organizational politics and centralization) and illustrated the two-way interactions. The significant cross-level interactions between big data attributes and contextual factors imply that the predictive power of innovation diffusion theory is contingent on organizational contexts.

Interestingly, the effects of contextual factor significant during the pre-adoption period but not the post-adoption period. This has not only offered empirical supports to the applicability of situational theory to explain individual acceptance of information technology, but also provide a complicated picture of the role of organizational politics and centralization over time. The varying effects of contextual factors in the innovation process provided new knowledge for future theory development connecting innovation diffusion theory and situational theory to explain individual acceptance of technology innovation.

Social capital theory and individual acceptance of information technology

Empirical findings in previous studies have shown the controversial effects of social capital constructs on individual acceptance of information technology. Some researchers included social influence in their frameworks (e.g. Taylor and Todd 1995; Venkatesh et al. 2003), whereas some others did not (e.g. Agarwal and Prasad 1997; Davis 1989). Some studies have shown the effects of social influence are contingent on organizational settings.

For example, Venkatesh and Davis (2000) found that the effects of social influence are significant in mandatory contexts. Some other studies found social influence has insignificant direct effects on individual acceptance of information technology. The effects were more contingent on demographics factors. For example, Venkatesh et al. (2003) showed that social influence did not have significant one-way effects on individual acceptance and usage generally, but it was more effective to elder people, particularly women.

The research has not only confirmed that social capital is critical to individual acceptance of information technology, but also specified the stages where social capital significantly affects individual adoption behaviors. The roles of social capital in the big data innovation process vary with the changes in the four conditions (i.e. opportunity, motivation, value expectancy and capability) mentioned by Nahapiet and Ghoshal (1998). During the pre-adoption period, the effects of social capital are not significant, because of the uncertain motivation and value expectancy of potential adopters. At the diffusion stage, the adoption of big data at the organizational level is a strong extrinsic motivator and thus individuals' intentions to use big data are contingent on their value perception. That is, at the diffusion stage, social capital and individuals' perception of big data interact and affect intention to use big data. At the implementation stage, the conditions of opportunity, motivation and value expectancy are met and thus social capital has direct facilitating effects on individuals' actual usage of big data. Combining views from both social capital and individual acceptance of information technology, this research has demonstrated that social capital becomes effective after the organizational adoption of big data. The effects of social capital are contingent on individuals' perceptions of big data during the diffusion stage, whereas at the implementation stage, the effects become direct and positive. The findings have provided a more process-based lens to study the relationship between social capital and individual acceptance of information technology, demonstrating the effects of social capital over timer and offering new knowledge together with empirical evidence for future theory development.

Data analytics innovation and performance

The current research has added new knowledge to data analytics literature through investigations on factors affect big data performance at the organizational level, as well as individual acceptance of big data. Literature on data analytics innovation diffusion has been limited, and studies on big data analytics are mainly qualitative. Bucklin and Gupta (1999) briefly touched berries to the diffusion of scan data analytics, such as insufficient advantages, high costs, unrealistic client expectations and organization size. But these factors were not examined with empirical evidence. Big data researchers suggest that factors such as a clear strategy, data-driven leadership, and organizational culture are critical to big data performance (e.g. Barton and Court 2012; Brown 2011; Bughin et al. 2011; McAfee and Brynjolfsson 2012). But few studies have provided empirical data and statistical analysis to support these assertions. To fill the void, the research examined the effects of three sources (i.e. big data attributes, organizational contexts and social capital) on individual acceptance of big data, and developed and tested a strategy-execution-performance framework to explain big data performance at the organizational level.

Data analytics innovation at the individual level. Applying innovation diffusion theory, situational theory and social capital theory, this research examined the effects of three sources (i.e. big data attributes, organizational contexts and consulting firms) on individual acceptance of big data. Results presented in Chapter 2 showed that big data attributes and contextual factors interact and affect individual acceptance of big data. Results presented in Chapter 3 demonstrated the variant roles of social capital in big data innovation process at the individual level. Consulting assets, the social capital derived from relationships with consulting firms, have insignificant effect on intention to adopt at the adoption stage. But at the diffusion stage, this social capital interacts with big data attributes and affect individual intention to use big data. At the implementation stage, the effects of consulting assets become direct on the actual usage of big data. The results have provided empirical evidence how analytics-level, organizational-level, and social-level constructs affect individual adoption and usage of big data.

Data analytics performance at the organizational level. The majority of big data performance literature have been based on fragmented qualitative analysis and not reached a unified theoretical framework. This study filled the gap by developing a strategy-execution-performance framework based on a systematic literature review and testing the framework with 200 questionnaires from 16 organizations and 78 external assessments from 15 consultants.

The results showed the important effects of strategic responsiveness, organizational contexts and execution process on big data performance. First, the results showed that strategic responsiveness was positively correlated with the evaluation of big data before the adoption and data driven decisions. However, the results indicated that the positive effects of strategic responsiveness decreases in centralized organizations. In centralized organizations, data-driven decisions were more often seen when organizations faced fierce competition. Second, the results showed decision process constructs (i.e. evaluation and data-driven decisions) were positively correlated to big data performance at the organizational level. The findings have not only confirmed the major assertions in previous big data studies (e.g. Barton and Court 2012; Brown 2011; Bughin et al. 2011; McAfee and Brynjolfsson 2012), but also provided empirical evidence on the strategy-execution-performance framework to explain and predict big data performance at the organizational level.

Managerial Implications

Increasing organizations have turned to big data analytics to extract customer insights and to increase profitability, but not many organizations understand how to proceed big data analytics (Barton and Court 2012) and even less have achieved promised big data performance (McAfee and Brynjolfsson 2012). This research addresses two issues, how to motivate employees to adopt and use big data and how to achieve high-level of big data performance. The results shed light on the effects of big data attributes, organizational contexts and social capital on individual acceptance of big data. The results also revealed the critical effects of organizational contexts and decision process on big data performance at the organizational level. These findings have offered not only theoretical guide but also empirical evidence on how to manage people and lead big data practice to achieve valuable results.

What motivates individuals to be data-driven?

Managers and employees' unwillingness to use data analytics is a major barrier to deriving valuable results from big data (Barton and Court 2012). For example, to optimize advertisement spending, a retail company invested massively on data analytics, which however was not used by frontline marketers to support marketing decisions (Barton and Court 2012). The reason was that these marketers did not understand data analytics and have little trust in the analytical model. Investigations into what factor motivates managers and employees to be data-driven are needed to guide big data practice.

The results of present research demonstrated the effects of three sources (e.g. big data attributes, organizational contexts and social capital) on individual acceptance of big data. The results showed that individual adoption and usage of big data were significantly affected by the perception of big data attributes. The correlations between big data attributes and individual acceptance were contingent on organizational contextual factors (e.g. strategic responsiveness, centralization and organizational politics). Moreover, the results presented in Chapter 3 showed that consulting assets, the social capital derived from relationships with consulting firms, enhanced the diffusion and implementation of big data at the individual level.

Big data attributes and individual acceptance. Individual acceptance of big data is significantly related to the perception of big data attributes. During the pre-adoption period, individuals' intentions to adopt big data are mainly correlated to their perceived relative advantage and trialability of big data. That it, the more benefits and the more chances to try big data, the more likelihood one adopts big data. The findings indicate that to motivate individuals to adopt big data, leaders should illustrate sufficient beneficial outcomes of big data and provide opportunities for big data trials and evaluation. Our interview findings show that the commonly used approach was to experiment big data on a small scale, based on which users' cases were developed and distributed to different teams. The users' cases provide information on how to exploit big data to support decisions and what outcomes can be achieved, allowing managers and employees to have more knowledge of the potential of big data.

Moreover, the perception of relative advantage and ease of use are related to individuals' intention to use big data during the post-adoption period. The findings suggest that individuals care more about the relative advantage and complexity when considering using big data or not. When big data is perceived beneficial and easy to use, individuals are more willing to use big data. Therefore, for those organizations that have adopted big data and are willing to motivate employees and managers to become data-driven, they should not only demonstrate the beneficial potential of big data to the managers and employees, but also make it as easy as possible to use big data. Big data analytics is a complicated process including data collection and cleaning, model development, result interpretation and decision-making (Barton and Court 2012). Big data analytics is easy for data scientists, not frontline managers who have more business knowledge than analytical skills. It is critical to make data analytics process simple enough and avoid technical and complicated terms when presenting analytical results.

The results also revealed the effects of trialability and compatibility on individuals' actual usage of big data. The actual usage is correlated with individuals' perception of trialability and compatibility. The findings suggest that to increase the usage of big data, leaders should provide more big data trial opportunities and also implement big data platform in a more compatible way with existing process.

Organizational context and individual acceptance. The effects of the two contextual factors (e.g. organizational politics and centralization) vary over time. The effects of contextual factors were significant during the pre-adoption period but not during the post-adoption period. For example, politics restrains the effects of information seeking and trialability, but enlarges that of relative advantage on the adoption of big data during the pre-adoption period. This is because data threatens game players' political control of decision-making process, but at the same time, analytics will be a powerful weapon against political manipulations. Such effects of politics suggest that leaders should carefully avoid the inefficient rejects of big data because of its low political acceptability, and appropriately use data analytics to weaken the inefficient political exercise that might harm organizational efficiency.

Consulting assets and individual acceptance. The findings suggest that consulting firms play a facilitating role after big data is adopted, rather than a motivating role. That is, interactions and resource exchanges with consulting firms do not increase marketers' willingness to adoption big data, but when marketers have decided the adoption, consultants will be brought in to assist the implementation of big data analytics. The statistical findings are consistent with our interview findings. For example, a consultant suggested that his clients usually came with decisions that had been made and seek assistants to implement the decisions.

How to achieve high-level of big data performance?

Managerial fads and fashions (Abrahamson 1991) might lead to the spending of millions of dollars without achieving promised returns. The past decades have witnessed the fads into several analytics innovation such as scanner data and customer relationship management system (Davenport et al. 2001). But not many organizations have successfully turned data into valuable results (Davenport et al. 2001). It is pressing to know what factor underpins data analytics performance.

The present research has showed the importance of strategic responsiveness, organizational context and execution process for big data performance. First, big data performance is significantly dependent on a thorough evaluation of big data and the use of big data analytics to support decisions. A thorough evaluation, through which managers and employees obtain more comprehensive knowledge of big data innovation, guarantees the rationality and efficiency of big data adoption. Data-driven decisions reflect the quality and actionability of analytical inputs into decisions and thus improve the value of decision outputs. The finding confirms that data-driven decisions yield better results (Barton and Court 2012; Davenport et al. 2001).

The results also showed the importance of strategic responsiveness and organizational contexts, namely centralization and competition intensity. Strategic responsiveness captures the degree to which organizations can proactively and quickly reacting to environmental changes. Strategic responsive organizations are more likely to thoroughly evaluation big data before the adoption, and use data analytics to support decisions. However, the positive correlation between strategic responsiveness and rational decision process is weaker in centralized organizations. That is, decentralized structure is a more favorable context for strategic responsiveness to be effective. Furthermore, the results demonstrated that the combination of centralization and intense competition encourages rational decision process. That it, when centralized organizations face intense competition, they are more likely to seek analytical supports when making decisions. Weaknesses of either big data strategy or execution will result in considerable loss in big data activities.

Limitations and Future Research

There are several limitations regarding current thesis. First, only some major factors were examined in current thesis, which might not provide a complete picture of big data innovation adoption and performance. Second, the target of only Australian individuals and organizations might delimit the generalization of the findings to other countries. Third, collecting data from single source in Study 1 and 2, and the use of self-assessed measures might generate biases. These limitations require further considerations and investigations, suggesting potential opportunities for future research.

The current study focuses on analytics attributes, organizational contexts and social capital affecting individual acceptance of big data, as well as strategic responsiveness, organizational contexts and execution process affecting big data performance. Although the current study does not provide a complete picture of big data innovation and performance, it should be a building block for future theory development and empirical investigation into data analytics. With regards to data analytics innovation, future researchers can explore other contextual factors that might constraint individual adoption and usage of data analytics. Regarding data analytics performance, the effects of other predictors, such as leadership, technological context or partnership supports (Bughin et al. 2011; Davenport et al. 2001; McAfee and Brynjolfsson 2012), can be tested. Harigopal (2006) suggested that organizational management researchers might consider a broad range of important factors relating to ecology, geography, politics, sociology, technology, economy and so forth. Future research might take these factors into consideration to enrich data analytics theories.

The targeted population of Study 1 and 2 is limited to individuals in Australia and that of Study 3 is limited to organizations in Australia. The sampling frame delimits the generalization of the research findings to other countries. Future researchers may consider investigating data analytics in a global context to achieve cross-cultural validation. Also, future researchers may consider compare data analytics innovation and performance from different regions to guide theory building and cross-cultural analytics practice.

In Study 1 and 2, data of independent and dependent variables were collected from the same source. One potential issue was common method bias, which might affect measure reliability and validity, and deflate or inflate observed relationships between independent and dependent variables (Podsakoff et al. 2003). In Study 3, data of independent and dependent variables were obtained from two sources, to a great extent decreasing the possibility of common method bias. However, given the use of self-assessment in all the three studies, the findings might be subjected to perception biases. Future research should search for more objective measures to capture data analytics innovation and performance.

As Study 1 and 2 used the same sample and similar dependent variables. Excluding some independent variables in the analysis of Study 1 and 2 might generate potential omitted variable bias. To measure the extent of the potential omitted variables bias, we have conducted the residual test in both of Study 1 and 2. The model residuals of Study 1 and 2 were not significantly related to corresponding independent variables, indicating that both studies suffer from least possible omitted variable bias.

Summary

This is the age of information. The competition is changed with the explosion of data. The society is growing with increasing demands for innovative products, services, and experience, all of which requires the inputs of customer insights. The emergence of big data has posed great opportunities to understand customers.

Organizations must understand how to motivate employees to become data-driven and how to achieve high-level of data analytics performance. Organizations performing well in data analytics are those that have the right organizational contexts, execution process and social capital. A right organizational context sets the overall tone for data analytics, strongly affecting employees' attitudes towards and use of data analytics. Organizational context also influences the diffusion and implementation of data analytics, as well as the performance. Moreover, to improve data analytics performance, organizations should also optimize the analytics execution process by reconciling the conflicts between decision makers and analysts. Lastly, organizations should understand the facilitating role of consulting firms and exploit social capital in an effective way.

At the center of big data innovation are the organizational leaders, who are responsible to form a right strategy, motivate employees to become data driven and to exploit big data to achieve higher performance. The initiation, adoption, and implementation of big data is not simple, but expensive, risky and time-consuming. But the potential is enormous. Insights from data will help the leaders to serve the customers much better, posing a significantly positive impact on employees, the organizations and the society.

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APPENDIX A: CONSENT FORM (INTERVIEW)

Participant Information and Consent Form

Name of Project: The Role of Social Capital in the Creation of Customer Knowledge

You are invited to participate in a study of *Social Capital and Customer Knowledge Creation.* The purpose of the study is to discover forms of social capital that have influences on the creation of customer knowledge. Specifically, we are interested in whether organizations' social networks can provide resources that facilitate the creation of customer knowledge and thus contribute to marketing competence.

The study is being conducted by Chu Wang (Email: chu.wang@mq.edu.au; Tel: 61-45 064 0806) to meet the requirements of Doctor of Philosophy in Marketing and Management, under the supervision of Prof. Mark Gabbott (Email: mark.gabbott@mq.edu.au; Tel: 61-2 9850 8554) and Prof. Scott Koslow (Email: scott.koslow@mq.edu.au; Tel: 61-2 9850 8459) of the Department of Marketing and Management, Macquarie University.

If you decide to participate, you will be asked to participate in a 40-minute interview to share your views on whether social networks can provide important resources, such as information and knowledge, which help organizations understand customer better. The audio of the interviews will be recorded to ensure that the transcription is complete and accurate. Despite the audio record, no other recording method will be used. There is no any risk to participants as a result of participations.

Any information or personal details gathered in the course of the study are confidential, except as required by law. No individual will be identified in any publication of the results. Only the chief investigator, co-investigator and the associate investigator of the project have access to the data. A summary of the results of the data can be made available to you on request to the associate investigator of this project, Chu Wang.

Participation in this study is entirely voluntary: you are not obliged to participate and if you decide to participate, you are free to withdraw at any time without having to give a reason and without consequence.

I,________________*(participant's name)* have read *(or, where appropriate, have had read to me)* and understand the information above and any questions I have asked have been answered to my satisfaction. I agree to participate in this research, knowing that I can withdraw from further participation in the research at any time without consequence. I have been given a copy of this form to keep.

Participant's Name:____
(Block letters)
Participant's Signature: ________________________ Date:__________________
Investigator's Name:____
(Block letters)
Investigator's Signature: ________________________ Date: __________________

The ethical aspects of this study have been approved by the Macquarie University Human Research Ethics Committee. If you have any complaints or reservations about any ethical aspect of your participation in this research, you may contact the Committee through the Director, Research Ethics (telephone (02) 9850 7854; email ethics@mq.edu.au). Any complaint you make will be treated in confidence and investigated, and you will be informed of the outcome.

APPENDIX B: CONSENT FORM (QUESTIONNAIRE)

Participant Information and Consent Form

Name of Project: Organizational Openness, Politics, Social Capital and the Use of Big Data

You are invited to participate in a study on *the Use of Big Data.* The purpose of the study is to discover how and why organizations accept and use big data in marketing activities. Specifically, we are interested in whether organizational openness to explore new ideas, the use of politics, and relationships with external consultants have influences on the relationships between characteristics of big data and the adoption of it to understand customers.

The study is being conducted by Chu Wang (Email: chu.wang@mq.edu.au; Tel: 61-45 064 0806) to meet the requirements of Doctor of Philosophy in Marketing and Management, under the supervision of Prof. Mark Gabbott (Email: mark.gabbott@mq.edu.au; Tel: 61-2 9850 8554) and Prof. Scott Koslow (Email: scott.koslow@mq.edu.au; Tel: 61-2 9850 8459) of the Department of Marketing and Management, Macquarie University.

If you decide to participate, you will be asked to fill in a questionnaire which consists of questions about the innovations in understanding customers and will take you about 25 to 30 minutes. Any information or personal details gathered in the questionnaire are confidential, except as required by law. There is no any risk to participants as a result of participations. No individual will be identified in any publication of the results. Only the chief investigator (Prof. Mark Gabbott), co-investigator (Prof. Scott Koslow) and the associate investigator (Chu Wang) of the project have the access to the data. A summary of the results of the data can be made available to you on request to the associate investigator of this project, Chu Wang.

Participation in this study is entirely voluntary: you are not obliged to participate and if you decide to participate, you are free to withdraw at any time without having to give a reason and without consequence. And you can choose the location that you prefer to conduct the survey.

I,______________________*(participant's name)* have read *(or, where appropriate, have had read to me)* and understand the information above and any questions I have asked have been answered to my satisfaction. I agree to participate in this research, knowing that I can withdraw from further participation in the research at any time without consequence. I have been given a copy of this form to keep.

Participant's Name:____
(Block letters)
Participant's Signature: ____________________________ Date:____________________
Investigator's Name:____
(Block letters)
Investigator's Signature: ____________________________ Date: ____________________

The ethical aspects of this study have been approved by the Macquarie University Human Research Ethics Committee. If you have any complaints or reservations about any ethical aspect of your participation in this research, you may contact the Committee through the Director, Research Ethics (telephone (02) 9850 7854; email ethics@mq.edu.au). Any complaint you make will be treated in confidence and investigated, and you will be informed of the outcome.

APPENDIX C: SURVEY INSTRUMENT FOR STUDY 1 AND STUDY 2

Big Data, What's the Big Deal?

MACQUARIE UNIVERSITY

Thank you for helping us with this study! We would like to know about your views of big data. This questionnaire has 4 sections and will take about 10 to 20 minutes.

SECTION 1 GENERAL INFORMATION

❖ **Please check the number to indicate your degree of agreement with the following statements:**

If your answer is…	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
Check the number	-3	-2	-1	0	1	2	3

Statements	Degree of Agreement						
I regularly explore information about markets.	-3	-2	-1	0	1	2	3
In our strategic planning process, the person doing the planning changes our strategic direction according to the market trends.	-3	-2	-1	0	1	2	3
If I wish to make my own decisions, I would be quickly discouraged.	-3	-2	-1	0	1	2	3
Whatever situation arises, we have procedures to follow in dealing with it.	-3	-2	-1	0	1	2	3
Competition in this product area is cut throat.	-3	-2	-1	0	1	2	3
In our department, senior management sometimes distort information.	-3	-2	-1	0	1	2	3
Some senior management have a hidden agenda.	-3	-2	-1	0	1	2	3
There is behind-the-scenes coalition building among proponents of particular views.	-3	-2	-1	0	1	2	3
Some managers co-opt other managers by giving tangible rewards to prevent oppositions.	-3	-2	-1	0	1	2	3
I often seek out information about new customer behavior trends.	-3	-2	-1	0	1	2	3
In the strategic planning process, our department emphasizes contingency plans.	-3	-2	-1	0	1	2	3
Even small matters of my job have to be referred to someone higher up for final answers.	-3	-2	-1	0	1	2	3
Everyone in this organization has a specific job to do.	-3	-2	-1	0	1	2	3
There are many promotion wars in this product area.	-3	-2	-1	0	1	2	3
In our department, senior management withhold information either partly or entirely.	-3	-2	-1	0	1	2	3
Some top management inappropriately control our agenda.	-3	-2	-1	0	1	2	3
Some senior management conduct secret meetings outside the formal chain of command to try to form alliances with key individuals.	-3	-2	-1	0	1	2	3
Some senior management use external experts to help legitimize their views.	-3	-2	-1	0	1	2	3
I frequently search for information about new ways to understand customers and markets.	-3	-2	-1	0	1	2	3
Our department adapts our strategy to customer and market trends.	-3	-2	-1	0	1	2	3
I have to ask my boss before I do almost anything.	-3	-2	-1	0	1	2	3
The organization keeps a written record of everyone's performance.	-3	-2	-1	0	1	2	3
Anything that one competitor can offer in this product area, others can match readily.	-3	-2	-1	0	1	2	3
In our department, information is unequally shared among different hierarchical levels.	-3	-2	-1	0	1	2	3
Senior managers sometimes drag their feet regarding the ideas they don't like.	-3	-2	-1	0	1	2	3
Co-optation has been used in our department to overcome resistance.	-3	-2	-1	0	1	2	3

Statements	Degree of Agreement						
External consultants are sometimes hired when they focus on solutions that meet our senior management's expectations.	-3	-2	-1	0	1	2	3
I actively look for information about new methods to understand consumers.	-3	-2	-1	0	1	2	3
Our strategy changes as markets change.	-3	-2	-1	0	1	2	3
Any decision I make has to have my boss' approval.	-3	-2	-1	0	1	2	3
We have to follow strict operating procedures at all times.	-3	-2	-1	0	1	2	3
Price competition is a hallmark in this area.	-3	-2	-1	0	1	2	3
In our department, employees at different hierarchical levels receive different information.	-3	-2	-1	0	1	2	3
Some top management pursue their own self-interests and squash other people's ideas.	-3	-2	-1	0	1	2	3
Some managers have privately attempted to transform other managers from opponents to supporters by co-opting them.	-3	-2	-1	0	1	2	3
Some staff build external alliances to push their views and influence internal decision-making.	-3	-2	-1	0	1	2	3
In our organization, whenever we have a problem we are supposed to go to the same person for an answer.	-3	-2	-1	0	1	2	3
One hears of a new competitive move in this product area almost every day.	-3	-2	-1	0	1	2	3
Our competitors in this product area are relatively weak.	-3	-2	-1	0	1	2	3
Some senior managers thwart the ideas they don't like.	-3	-2	-1	0	1	2	3
Some individuals band together to influence decision-making process in our department.	-3	-2	-1	0	1	2	3
The senior managers ally with their proponents to push their views.	-3	-2	-1	0	1	2	3
Some managers co-opt those with potential to hinder their goals.	-3	-2	-1	0	1	2	3
Some managers have had their ideas co-opted by other managers.	-3	-2	-1	0	1	2	3
If the result, offered by external consultants, does not meet our managers' expectation, it will not be used.	-3	-2	-1	0	1	2	3

SECTION 2: SOURCES OF CUSTOMER AND MARKET INFORMATION

❖ **Please tick or circle the number to indicate: 1) Which of the following played important roles as sources of information to understand customers and markets; 2) The interaction frequency, participation frequency or your usage of these sources; and 3) how much do you trust these sources.**

1) If the source is…	Not at all important	Very unimportant	Somewhat unimportant	Neutral	Somewhat important	Very important	Extremely important
Please check the number…	-3	-2	-1	0	1	2	3

2) If the frequency is…	Never	Hardly ever	Sometimes	Often	Usually	Nearly Always
Please check the number…	0	1	2	3	4	5

3) If the degree of trust is…	None	Very low	Low	Medium	High	Very high
Please check the number…	0	1	2	3	4	5

Sources of Information	1) The importance of the source…							2) The frequency you interact with, participate in or use…						3) The degree you trust the sources…					
Clients	-3	-2	-1	0	1	2	3	0	1	2	3	4	5	0	1	2	3	4	5
Suppliers	-3	-2	-1	0	1	2	3	0	1	2	3	4	5	0	1	2	3	4	5
Competitors	-3	-2	-1	0	1	2	3	0	1	2	3	4	5	0	1	2	3	4	5
Suppliers of software	-3	-2	-1	0	1	2	3	0	1	2	3	4	5	0	1	2	3	4	5
Market research firms	-3	-2	-1	0	1	2	3	0	1	2	3	4	5	0	1	2	3	4	5
Consulting firms	-3	-2	-1	0	1	2	3	0	1	2	3	4	5	0	1	2	3	4	5
Search engine organizations (such as Google Analytics)	-3	-2	-1	0	1	2	3	0	1	2	3	4	5	0	1	2	3	4	5
Universities	-3	-2	-1	0	1	2	3	0	1	2	3	4	5	0	1	2	3	4	5
Fairs/ exhibitions	-3	-2	-1	0	1	2	3	0	1	2	3	4	5	0	1	2	3	4	5
Marketing associations	-3	-2	-1	0	1	2	3	0	1	2	3	4	5	0	1	2	3	4	5
Industry meetings	-3	-2	-1	0	1	2	3	0	1	2	3	4	5	0	1	2	3	4	5
Marketing publications	-3	-2	-1	0	1	2	3	0	1	2	3	4	5	0	1	2	3	4	5
Internet	-3	-2	-1	0	1	2	3	0	1	2	3	4	5	0	1	2	3	4	5
External databases	-3	-2	-1	0	1	2	3	0	1	2	3	4	5	0	1	2	3	4	5
Other important sources (Please indicate):__________	-3	-2	-1	0	1	2	3	0	1	2	3	4	5	0	1	2	3	4	5

SECTION 3: THE USE OF BIG DATA

❖ **This section focuses on Big Data. Do you know what big data is? Please check only one box.**

☐ No, never heard of it. ☐ No, heard of it but really don't understand it.
☐ Yes, but only a little. ☐ Yes, somewhat. ☐ Yes, a lot.

Big Data describes the exponential growth and availability of data that are generated from transactional system, mobile devices, web clickstreams, machine sensors, and virtually anything that generates an electrical pulse, or could be purchased from external third party. Big data is of high volume, high velocity and high complexity.

❖ **Given this definition of big data, do you know what big data is now?**

☐ Yes, but I already knew what it was. ☐ Yes, but I use a different term for big data (please indicate__________)
☐ Yes, I somewhat understand big data now. ☐ No, still don't know (go to Section 4).

❖ **We would like to know about your perceptions of big data at two points of time: pre-adoption period and post-adoption period. <u>If you haven't started to use big data, just check the number in the "Pre-adoption period" column.</u>**

If your answer is…	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
Check the number	-3	-2	-1	0	1	2	3

Your views of big data…	Degree of Agreement													
	Pre-adoption period							Post-adoption period						
Big data gave/gives me great insights into market & customer changes.	-3	-2	-1	0	1	2	3	-3	-2	-1	0	1	2	3
Big data was/is compatible with most aspects of my work.	-3	-2	-1	0	1	2	3	-3	-2	-1	0	1	2	3
I believe that it is easy to use big data to do what I want it to do.	-3	-2	-1	0	1	2	3	-3	-2	-1	0	1	2	3
People would have little difficulty illustrating the benefits of analyzing big data.	-3	-2	-1	0	1	2	3	-3	-2	-1	0	1	2	3

Your views of big data…	Degree of Agreement													
	Pre-adoption period							**Post-adoption period**						
I was/am permitted to use big data on a trial basis long enough to see what it could do.	-3	-2	-1	0	1	2	3	-3	-2	-1	0	1	2	3
I intended/intend to use big data.	-3	-2	-1	0	1	2	3	-3	-2	-1	0	1	2	3
Big data enabled/enables me to gain insights into consumers more quickly.	-3	-2	-1	0	1	2	3	-3	-2	-1	0	1	2	3
Big data fitted/fits well with the way I like to work.	-3	-2	-1	0	1	2	3	-3	-2	-1	0	1	2	3
Learning to operate big data system was/is easy for me.	-3	-2	-1	0	1	2	3	-3	-2	-1	0	1	2	3
Others could/can show me the consequences of analyzing big data.	-3	-2	-1	0	1	2	3	-3	-2	-1	0	1	2	3
Before deciding whether to use big data, I had/have many opportunities to try various big data approaches.	-3	-2	-1	0	1	2	3	-3	-2	-1	0	1	2	3
I predicted/predict that I would use big data in the future.	-3	-2	-1	0	1	2	3	-3	-2	-1	0	1	2	3
Big data improved/improves the quality of my understanding of markets and customers.	-3	-2	-1	0	1	2	3	-3	-2	-1	0	1	2	3
Big data fitted/fits into my work style.	-3	-2	-1	0	1	2	3	-3	-2	-1	0	1	2	3
How I would interact with big data was/is clear and understandable.	-3	-2	-1	0	1	2	3	-3	-2	-1	0	1	2	3
From watching others who using big data, the value of analyzing big data was/is apparent to me.	-3	-2	-1	0	1	2	3	-3	-2	-1	0	1	2	3
Before deciding whether or not to use big data, I was/am able to properly try out big data solutions.	-3	-2	-1	0	1	2	3	-3	-2	-1	0	1	2	3
I knew/know where I can go to satisfactorily try out various uses of big data.	-3	-2	-1	0	1	2	3	-3	-2	-1	0	1	2	3
If I had/have the power to decide whether to use big data, I would say yes.	-3	-2	-1	0	1	2	3	-3	-2	-1	0	1	2	3
Big data made/makes it easier to understand consumers.	-3	-2	-1	0	1	2	3	-3	-2	-1	0	1	2	3
Overall, I believe that big data is easy to use.	-3	-2	-1	0	1	2	3	-3	-2	-1	0	1	2	3
Big data was/is compatible with the current process of my work.	-3	-2	-1	0	1	2	3	-3	-2	-1	0	1	2	3
Others had/have difficulties demonstrating to me why analyzing big data may or may not be beneficial.	-3	-2	-1	0	1	2	3	-3	-2	-1	0	1	2	3
Big data solutions were/are available to me such that I could adequately test run various applications.	-3	-2	-1	0	1	2	3	-3	-2	-1	0	1	2	3
I was/am hoping to apply big data for my work.	-3	-2	-1	0	1	2	3	-3	-2	-1	0	1	2	3
At present, I consider myself to be a frequent user of big data.								-3	-2	-1	0	1	2	3
At present, I use big data for my work regularly.								-3	-2	-1	0	1	2	3
I currently use big data routinely for my work.								-3	-2	-1	0	1	2	3
Big data has now become a regular part of my work.								-3	-2	-1	0	1	2	3

❖ **We would like to know about your views of big data before you started to use it. If you are using big data now, please think back to the time just before your organization started using big data, check the ☐ and answer the questions on the left column. If you haven't started to use big data, please check the ☐ and answer the questions on the right column.**

If your answer is…	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
Check the number	-3	-2	-1	0	1	2	3

☐ **If you are using big data now….**	**Degree of Agreement**	☐ **If you haven't started to use big data….**
I was aware of big data.	-3 -2 -1 0 1 2 3	I am aware of big data.
I understood the value of big data.	-3 -2 -1 0 1 2 3	I understand the value of big data.
I considered big data's suitability for my organization.	-3 -2 -1 0 1 2 3	I have considered big data's suitability for my organization.
I discussed big data informally with my colleagues.	-3 -2 -1 0 1 2 3	I have discussed big data informally with my colleagues.
The trial of big data was initiated before the decision to adopt.	-3 -2 -1 0 1 2 3	The trial of big data has been initiated.
Before deciding whether to use them, big data approaches were used in a small scale to see whether they could work.	-3 -2 -1 0 1 2 3	Big data has been used in a small scale to see whether it could fix some organizational problems.
We trialled big data so to evaluate its potential value before deciding whether to use it.	-3 -2 -1 0 1 2 3	We have trialled big data so to evaluate its potential value before deciding whether to use it.
Big data was evaluated according to financial and/or strategic criteria before deciding whether to use it.	-3 -2 -1 0 1 2 3	Big data has been evaluated according to financial and/or strategic criteria.
The adoption of big data has been approved.	-3 -2 -1 0 1 2 3	
We made the decision to adopt big data.	-3 -2 -1 0 1 2 3	
A big data system was designed to fit our department's situation and problems.	-3 -2 -1 0 1 2 3	
Our department's roles and responsibilities were altered to accommodate big data.	-3 -2 -1 0 1 2 3	
Big data has been widely introduced within our department.	-3 -2 -1 0 1 2 3	
Big data has been incorporated into the regular activities of our department.	-3 -2 -1 0 1 2 3	
Big data has been well accepted and frequently used in our department.	-3 -2 -1 0 1 2 3	
Employees of our department use big data routinely.	-3 -2 -1 0 1 2 3	
Big data has become a normal and routine part of our department.	-3 -2 -1 0 1 2 3	

SECTION 4: RESPONDENT INFORMATION

Demographic information is important for our analysis. All information will be kept confidential.

Department:________________________________; Job Title:________________________________ ;
Years in firm: ________________________________; Years in industry: ________________________________ ;
Gender: ________________________________; Age : ________________________________ ;
Highest level of Education:________________________________; Ethnicity: ________________________________ ;
Level of Hierarchy in current organization: ☐ 7 (Highest-level management such as CEO); ☐ 6 (other executive-level management); ☐ 5 (high-level management such as department managers); ☐ 4 (mid-level management such coordinators); ☐ 3 (lower-level management such as specialists and executives); ☐ 2 (e.g. senior employees); ☐ 1 (entry-level employees such as trainees).

APPENDIX D: SURVEY INSTRUMENT FOR EXTERNAL ASSESSMENTS IN STUDY 3

Big Data Performance Assessment

The value extracted from big data by your clients.

❖ Please indicate the organization that you would like to review, and indicate your degree of agreement with the following statements concerning this organization: ______________________.

Statements	**Degree of Agreement** Strongly disagree	Somewhat disagree	Neutral	Somewhat agree	Strongly agree
Potentially, good market and customer insights can be extracted from big data that this organization has.	☐	☐	☐	☐	☐
This organization has successfully extracted good market and customer insights from big data.	☐	☐	☐	☐	☐
This organization has the potential to take great advantage of big data.	☐	☐	☐	☐	☐
This organization has already taken great advantage of big data.	☐	☐	☐	☐	☐
Potentially, desirable outcomes can be achieved by using big data.	☐	☐	☐	☐	☐
The actual outcomes of using big data by this organization are positive.	☐	☐	☐	☐	☐
Big data can potentially generate great value for this organization.	☐	☐	☐	☐	☐
The value of big data is well achieved by this organization.	☐	☐	☐	☐	☐

RESPONDENT INFORMATION

Demographic information is important for our analysis. All the information gathered will be kept confidential.

Department:______________________________ ; Job Title: ______________________________ ;

Years in firm: ______________________________ ; Years in industry:______________________________ ;

Gender: ______________________________ ; Age :______________________________ ;

Highest level of Education:____________________ ; Ethnicity: ______________________________ ;

Level of Hierarchy in current organization: ☐ 7 (Highest-level management such as CEO); ☐ 6 (other executive-level management); ☐ 5 (high-level management such as department managers); ☐ 4 (mid-level management such coordinators); ☐ 3 (lower-level management such as specialists and executives); ☐ 2 (e.g. senior employees); ☐ 1 (entry-level employees such as trainees).

APPENDIX E: SURVEY INSTRUMENT FOR INTERNAL ASSESSMENTS IN STUDY 3

Big Data, What's the Big Deal?

Thank you for helping us with this study! We would like to know about your views of big data analytics. This questionnaire has 3 sections and will take about 10 minutes.

Section 1: General information

❖ **Please check the number to indicate your degree of agreement with the following statements:**

If your answer is…	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
Check the number	-3	-2	-1	0	1	2	3

Statements	Degree of Agreement						
I have recently explored new information about markets.	-3	-2	-1	0	1	2	3
In our strategic planning process, the person doing the planning makes appropriate changes of our strategic direction.	-3	-2	-1	0	1	2	3
If I wish to make my own decisions, I would be quickly discouraged.	-3	-2	-1	0	1	2	3
Competition in this product area is cut throat.	-3	-2	-1	0	1	2	3
In our department, senior management sometimes distort information.	-3	-2	-1	0	1	2	3
I often seek out new customer behavior trends.	-3	-2	-1	0	1	2	3
In the strategic planning process, our department emphasizes contingency plans.	-3	-2	-1	0	1	2	3
Even small matters of my job have to be referred to someone higher up for final answers.	-3	-2	-1	0	1	2	3
There are many promotion wars in this product area.	-3	-2	-1	0	1	2	3
I actively search for new ways to understand customers and markets.	-3	-2	-1	0	1	2	3
Our department adapts our strategy to customer and market trends.	-3	-2	-1	0	1	2	3
I have to ask my boss before I do almost anything.	-3	-2	-1	0	1	2	3
Anything that one competitor can offer in this product area, others can match readily.	-3	-2	-1	0	1	2	3
I try out new methods to understand consumers.	-3	-2	-1	0	1	2	3
Our strategy changes as markets change.	-3	-2	-1	0	1	2	3
Any decision I make has to have my boss' approval.	-3	-2	-1	0	1	2	3
Price competition is a hallmark in this area.	-3	-2	-1	0	1	2	3
Competition in this product area is cut throat.	-3	-2	-1	0	1	2	3
Our competitors in this product area are relatively weak.	-3	-2	-1	0	1	2	3
Some top management pursue their own self-interests and squash other people's ideas.	-3	-2	-1	0	1	2	3
Some staff build external alliances to push their views and influence internal decision-making.	-3	-2	-1	0	1	2	3
The senior managers ally with their proponents to push their views.	-3	-2	-1	0	1	2	3
Some managers co-opt those with potential to hinder their goals.	-3	-2	-1	0	1	2	3

Section 2: The Use of Big Data

❖ **We would like to know about your perceptions of big data.**

If your answer is…	**Strongly disagree**	**Disagree**	**Somewhat disagree**	**Neutral**	**Somewhat agree**	**Agree**	**Strongly agree**
Check the number	**-3**	**-2**	**-1**	**0**	**1**	**2**	**3**

Your views of big data…	Degree of Agreement						
Big data gives me great insights into market & customer changes.	-3	-2	-1	0	1	2	3
Big data is compatible with most aspects of my work.	-3	-2	-1	0	1	2	3
I believe that it is easy to use big data to do what I want it to do.	-3	-2	-1	0	1	2	3
People would have little difficulty illustrating the benefits of analyzing big data.	-3	-2	-1	0	1	2	3
I am permitted to use big data on a trial basis long enough to see what it could do.	-3	-2	-1	0	1	2	3
I intend to use big data.	-3	-2	-1	0	1	2	3
Big data enables me to gain insights into consumers more quickly.	-3	-2	-1	0	1	2	3
Big data fits well with the way I like to work.	-3	-2	-1	0	1	2	3
Learning to operate big data system is easy for me.	-3	-2	-1	0	1	2	3
Others can show me the consequences of analyzing big data.	-3	-2	-1	0	1	2	3
Before deciding whether to use big data, I had many opportunities to try various big data approaches.	-3	-2	-1	0	1	2	3
I predict that I would use big data in the future.	-3	-2	-1	0	1	2	3
Big data improves the quality of my understanding of markets and customers.	-3	-2	-1	0	1	2	3
Big data fits into my work style.	-3	-2	-1	0	1	2	3
How I would interact with big data was/is clear and understandable.	-3	-2	-1	0	1	2	3
From watching others who using big data, the value of analyzing big data is apparent to me.	-3	-2	-1	0	1	2	3
Before deciding whether or not to use big data, I am able to properly try out big data solutions.	-3	-2	-1	0	1	2	3
I know where I can go to satisfactorily try out various uses of big data.	-3	-2	-1	0	1	2	3
If I have the power to decide whether to use big data, I would say yes.	-3	-2	-1	0	1	2	3
Big data makes it easier to understand consumers.	-3	-2	-1	0	1	2	3
Overall, I believe that big data is easy to use.	-3	-2	-1	0	1	2	3
Big data is compatible with the current process of my work.	-3	-2	-1	0	1	2	3
Others have difficulties demonstrating to me why analyzing big data may or may not be beneficial.	-3	-2	-1	0	1	2	3
Big data solutions are available to me such that I could adequately test run various applications.	-3	-2	-1	0	1	2	3
I am hoping to apply big data for my work.	-3	-2	-1	0	1	2	3
At present, I consider myself to be a frequent user of big data.	-3	-2	-1	0	1	2	3
Without the insights from data, the decisions we have made would have been different.	-3	-2	-1	0	1	2	3
I currently use big data routinely for my work.	-3	-2	-1	0	1	2	3
Big data has now become a regular part of my work.	-3	-2	-1	0	1	2	3
The majority of the results from data analytics are used to support the d ecision-making.	-3	-2	-1	0	1	2	3
At present, I use big data for my work regularly.	-3	-2	-1	0	1	2	3

❖ **We would like to know about the assimilation of big data in your organization.**

If your answer is…	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
Check the number	-3	-2	-1	0	1	2	3

If you are using big data now….	**Degree of Agreement**						
I was aware of big data.	-3	-2	-1	0	1	2	3
I understood the value of big data.	-3	-2	-1	0	1	2	3
I considered big data's suitability for my organization.	-3	-2	-1	0	1	2	3
I discussed big data informally with my colleagues.	-3	-2	-1	0	1	2	3
The trial of big data was initiated before the decision to adopt.	-3	-2	-1	0	1	2	3
Before deciding whether to use them, big data approaches were used in a small scale to see whether they could work.	-3	-2	-1	0	1	2	3
We trialled big data so to evaluate its potential value before deciding whether to use it.	-3	-2	-1	0	1	2	3
Big data was evaluated according to financial and/or strategic criteria before deciding whether to use it.	-3	-2	-1	0	1	2	3
The adoption of big data has been approved.	-3	-2	-1	0	1	2	3
We made the decision to adopt big data.	-3	-2	-1	0	1	2	3
A big data system was designed to fit our department's situation and problems.	-3	-2	-1	0	1	2	3
Our department's roles and responsibilities were altered to accommodate big data.	-3	-2	-1	0	1	2	3
Big data has been widely introduced within our department.	-3	-2	-1	0	1	2	3
Big data has been incorporated into the regular activities of our department.	-3	-2	-1	0	1	2	3
Big data has been well accepted and frequently used in our department.	-3	-2	-1	0	1	2	3
Employees of our department use big data routinely.	-3	-2	-1	0	1	2	3
Big data has become a normal and routine part of our department.	-3	-2	-1	0	1	2	3
Few decisions would have been made without data analytics.	-3	-2	-1	0	1	2	3
The results of the data analytics have significant effects on the decision-making process.	-3	-2	-1	0	1	2	3

Section 3: Respondent Information

Demographic information is important for our analysis. All the information gathered will be kept confidential.

Department:________________________________ ; Job Title: ___________________________________ ;

Years in firm: ______________________________ ; Years in industry:_____________________________ ;

Gender: __________________________________ ; Age :____ ;

Highest level of Education:____________________ ; Ethnicity: ___________________________________ ;

Level of Hierarchy in current organization: ☐ 7 (Highest-level management such as CEO); ☐ 6 (other executive-level management); ☐ 5 (high-level management such as department managers); ☐ 4 (mid-level management such coordinators); ☐ 3 (lower-level management such as specialists and executives); ☐ 2 (e.g. senior employees); ☐ 1 (entry-level employees such as trainees).

APPENDIX F: ETHICS APPROVAL

(REFERENCE NUMBER: 5201300692)

MACQUARIE University

CHU WANG <chu.wang2@students.mq.edu.au>

Approved

Mrs Yanru Ouyang <yanru.ouyang@mq.edu.au> Fri, Nov 1, 2013 at 1:55 PM
To: Professor Mark Gabbott <mark.gabbott@mq.edu.au>
Cc: Dr Scott Koslow <scott.koslow@mq.edu.au>, Mrs Chu Wang <chu.wang2@students.mq.edu.au>

Dear Professor Gabbott,

Re: 'Organizational Openness, politics, social capital and innovations in customer knowledge creation.'

Reference No.: 5201300692

Thank you for your recent correspondence. Your response has addressed the issues raised by the Faculty of Business & Economics Human Research Ethics Sub Committee. Approval of the above application is granted, effective "29/10/2013". This email constitutes ethical approval only.

This research meets the requirements of the National Statement on Ethical Conduct in Human Research (2007). The National Statement is available at the following web site:

http://www.nhmrc.gov.au/_files_nhmrc/publications/attachments/e72.pdf.

The following personnel are authorised to conduct this research:

Dr Scott Koslow
Mrs Chu Wang
Professor Mark Gabbott

NB. STUDENTS: IT IS YOUR RESPONSIBILITY TO KEEP A COPY OF THIS APPROVAL EMAIL TO SUBMIT WITH YOUR THESIS.

Please note the following standard requirements of approval:

1. The approval of this project is conditional upon your continuing compliance with the National Statement on Ethical Conduct in Human Research (2007).

2. Approval will be for a period of five (5) years subject to the provision of annual reports.

Progress Report 1 Due: 29th Oct. 2014
Progress Report 2 Due: 29th Oct. 2015
Progress Report 3 Due: 29th Oct. 2016
Progress Report 4 Due: 29th Oct. 2017
Final Report Due: 29th Oct. 2018

NB. If you complete the work earlier than you had planned you must submit a Final Report as soon as the work is completed. If the project has been discontinued or not commenced for any reason, you are also required to submit a Final Report for the project.

Progress reports and Final Reports are available at the following website:

http://www.research.mq.edu.au/for/researchers/how_to_obtain_ethics_approval/human_research_ethics/forms

3. If the project has run for more than five (5) years you cannot renew approval for the project. You will need to complete and submit a Final Report and submit a new application for the project. (The five year limit on renewal of approvals allows the Committee to fully re-review research in an environment where legislation, guidelines and requirements are continually changing, for example, new child protection and privacy laws).

4. All amendments to the project must be reviewed and approved by the Committee before implementation. Please complete and submit a Request for Amendment Form available at the following website:

http://www.research.mq.edu.au/for/researchers/how_to_obtain_ethics_approval/human_research_ethics/forms

5. Please notify the Committee immediately in the event of any adverse effects on participants or of any unforeseen events that affect the continued ethical acceptability of the project.

6. At all times you are responsible for the ethical conduct of your research in accordance with the guidelines established by the University. This information is available at the following websites:

http://www.mq.edu.au/policy/
http://www.research.mq.edu.au/for/researchers/how_to_obtain_ethics_approval/human_research_ethics/policy

If you will be applying for or have applied for internal or external funding for the above project it is your responsibility to provide the Macquarie University's Research Grants Management Assistant with a copy of this email as soon as possible. Internal and External funding agencies will not be informed that you have approval for your project and funds will not be released until the Research Grants Management Assistant has received a copy of this email.

If you need to provide a hard copy letter of approval to an external organisation as evidence that you have approval, please do not hesitate to contact the FBE Ethics Committee Secretariat, via fbe-ethics@mq.edu.au or 9850 4826.

Please retain a copy of this email as this is your official notification of ethics approval.

Yours sincerely,

Parmod Chand
Chair, Faculty of Business and Economics Ethics Sub-Committee
Faculty of Business and Economics
Level 7, E4A Building
Macquarie University
NSW 2109 Australia
T: +61 2 9850 4826
F: +61 2 9850 6140
www.businessandeconomics.mq.edu.au/

APPENDIX G: ETHICS APPROVAL

(REFERENCE NUMBER: 5201300405)

MACQUARIE University

CHU WANG <chu.wang2@students.mq.edu.au>

Approved - 5201300405

Mrs Yanru Ouyang <yanru.ouyang@mq.edu.au> Fri, Jun 14, 2013 at 4:48 PM
To: Professor Mark Gabbott <mark.gabbott@mq.edu.au>
Cc: Dr Scott Koslow <scott.koslow@mq.edu.au>, Mrs Chu Wang <chu.wang2@students.mq.edu.au>

Dear Professor Gabbott,

Re: 'The Role of Social Capital in the creation of customer knowledge.'

Reference No.: 5201300405

Thank you for your recent correspondence. Your response has addressed the issues raised by the Faculty of Business & Economics Human Research Ethics Sub Committee. Approval of the above application is granted, effective "14/06/2013". This email constitutes ethical approval only.

This research meets the requirements of the National Statement on Ethical Conduct in Human Research (2007). The National Statement is available at the following web site:

http://www.nhmrc.gov.au/_files_nhmrc/publications/attachments/e72.pdf.

The following personnel are authorised to conduct this research:

Dr Scott Koslow
Mrs Chu Wang
Professor Mark Gabbott

NB. STUDENTS: IT IS YOUR RESPONSIBILITY TO KEEP A COPY OF THIS APPROVAL EMAIL TO SUBMIT WITH YOUR THESIS.

Please note the following standard requirements of approval:

1. The approval of this project is conditional upon your continuing compliance with the National Statement on Ethical Conduct in Human Research (2007).

2. Approval will be for a period of five (5) years subject to the provision of annual reports.

Progress Report 1 Due: 14th Jun 2014
Progress Report 2 Due: 14th Jun 2015
Progress Report 3 Due: 14th Jun 2016
Progress Report 4 Due: 14th Jun 2017
Final Report Due: 14th Jun 2018

NB. If you complete the work earlier than you had planned you must submit a Final Report as soon as the work is completed. If the project has been discontinued or not commenced for any reason, you are also required to submit a Final Report for the project.

Progress reports and Final Reports are available at the following website:

http://www.research.mq.edu.au/for/researchers/how_to_obtain_ethics_approval/human_research_ethics/forms

3. If the project has run for more than five (5) years you cannot renew approval for the project. You will need to complete and submit a Final Report and submit a new application for the project. (The five year limit on renewal of approvals allows the Committee to fully re-review research in an environment where legislation, guidelines and requirements are continually changing, for example, new child protection and privacy laws).

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5. Please notify the Committee immediately in the event of any adverse effects on participants or of any unforeseen events that affect the continued ethical acceptability of the project.

6. At all times you are responsible for the ethical conduct of your research in accordance with the guidelines established by the University. This information is available at the following websites:

http://www.mq.edu.au/policy/
http://www.research.mq.edu.au/for/researchers/how_to_obtain_ethics_approval/human_research_ethics/policy

If you will be applying for or have applied for internal or external funding for the above project it is your responsibility to provide the Macquarie University's Research Grants Management Assistant with a copy of this email as soon as possible. Internal and External funding agencies will not be informed that you have approval for your project and funds will not be released until the Research Grants Management Assistant has received a copy of this email.

If you need to provide a hard copy letter of approval to an external organisation as evidence that you have approval, please do not hesitate to contact the FBE Ethics Committee Secretariat, via fbe-ethics@mq.edu.au or 9850 4826.

Please retain a copy of this email as this is your official notification of ethics approval.

Yours sincerely,

Parmod Chand
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