Three Essays on Big Data Adoption and Its Impact on Business Value Creation

By

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Abstract

Big data has received much attention from firm executives, government officials, and academic scholars in the last few years. It offers firms new opportunities to develop competitive advantage. Big data can play an important role in revolutionizing and streamlining business in the current volatile environment. Thus, the adoption and implementation of big data is critical to business success.

Essay 1 presents a meta-analysis of big data use and its impact on business value creation and develops a big data use effects framework. As extant research expands, the impact of big data is becoming more evident. However, it is beneficial to review empirical research results to develop a better understanding of these impacts. Essay 1 presents a meta-analysis literature review of current big data literature that investigates the impacts of big data. Using this review, we develop a big data use effects framework that offers directions for future research.

Essay 2 investigates the relationship between organizational readiness for change and intention to adopt big data in a turbulent environment. A theoretical framework, grounded in open-systems theory, is used to examine the relationships among organizational readiness for change, market turbulence, and intention to adopt big data. Appropriateness, management support, change self-efficacy, and personal valence positively influence the big data adoption intention. Market turbulence partially moderates the relationship between organizational readiness for change and the intention to adopt big data. The findings provide theoretical and managerial implications.

Essay 3 presents an examination of the relationships among big data capabilities, organizational decision making, and business value creation. Using big data innovation to create business value is a challenge for practitioners, especially in turbulent business environments. Drawing on a process-level business value creation view and the dynamic capabilities perspective, we investigate the use of big data in creating business value through organizational decision making quality improvement. The moderating role of organizational innovativeness is discussed. The findings offer a better understanding of big data use in practice.

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List of Abbreviations

AVE	Average Variance Extracted
BDA	Big Data Analytics
BDC	Big Data Capability
CFI	Comparative Fit Index
CR	Construct Reliability
DCV	Dynamic Capability View
DDDM	Data-driven Decision Making
IS	Information Systems
IFI	Incremental Fit Index
IT	Information Technology
KBV	Knowledge Based View
MCAR	Missing Completely At Random
MIS	Management Information System
PLS	Partial Least Square
RMSEA	Root Mean Square Error of Approximation
RBV	Resources Based View
SEM	Structural Equation Modeling
TLI	Tucker Lewis Index
VIF	Variance Inflation Factor

ESSAY 1: A META-ANALYSIS OF ON BIG DATA USE AND ITS IMPACT ON BUSINESS VALUE CREATION

Introduction

In recent years, big data has become a common topic for businesses. Differentiated from traditional data management and analysis by its ability to facilitate data volume, variety and velocity (Manyika et al., 2011), big data is promoted as a way for businesses to promote growth, increase performance, and gain competitive advantage. When the business environment is fast-moving and competitive, managers look for ways to gain value from their various information assets and to increase the quality of their decision making. This requires advanced technologies and analytic techniques to facilitate the breadth and variety of an organization's data sources. The benefits of data-driven decision making (DDDM) have been widely demonstrated (Provost & Fawcett, 2013). Big data plays an important role in revolutionizing how managers can leverage information assets during decision making (McAfee & Brynjolfsson, 2012).

Leveraging information and advanced analytics to make high quality decisions, and acting appropriately on those decisions, will enable organizations to increase business value. These increases in business value may be evident in many different areas of an organization, such as product and operations management, marketing development, customer demand prediction, and decision making optimization. How and to what extent the use of big data processes will affect organization outcomes such as performance needs further investigation.

Whether implementing big data is the correct course of action for all businesses is still being debated. Some scholars argue that firms may not benefit enough from big data process outcomes to offset the often large investment that is required; further, the difficulty inherent in

turning insights into competitive advantage may reduce the quality of the outcome (Ross, Beath, & Quaadgras, 2013). How to successfully leverage business analytics processes to gain business value needs deeper analysis (Sharma, Mithas, & Kankanhalli, 2014).

In the last few years, many organizations have invested in big data infrastructures for a number of reasons. For example, Schroeck et al. (2012) found that 49% of organizations anticipate customer-centric outcomes by using big data, 18% expect operational optimization, 15% expect enhancement of risk/financial management, 14% hope to create a new business model, and 4% expect to improve employee collaboration. Another study investigated firms that have implemented big data and found that 72% of them leverage big data for customer domains, 45% for supply chain domains and 35% for competition domains (Bughin, 2016).

More scholars are beginning to discuss big data impact on business value (Mikalef et al., 2017; Sharma, Mithas, & Kankanhalli, 2014). Big data can be implemented across industries, and in an organization, across business units, including operations management, production,and customer and supplier relationship (Manyika et al., 2011). Wamba et al. (2015) utilized a systematic review and a longitudinal case study to develop an interpretive framework. Their work sheds light on big data applications and their role in generating business value. Akter & Wamba (2016) reviewed big data use in e-commerce while Xu, Frankwick & Ramirez discuss big data use for improving new product success (2016). To date, there is lack of agreement about how big data processes contribute to firm performance, especially with regard to business value creation.

This is an area that needs further investigation. For example, effective use of organizational resources, socio-technological developments, and how big data should be incorporated into strategic and tactical are areas that are underdeveloped (Mikalef et al., 2017).

To fully understand what academics have uncovered and where the gaps in research exist, it is useful to examine extant research with an eye toward impacts of big data processes. Thus, there is a need to review current empirical research results and develop a better understanding of big data impacts. In response, we conduct a review of current big data literature for evidence of impact. From there, we develop a big data use-effects framework.

Review of Literature

Review of Big Data Definition in the Business Context

To begin to understand the role of big data in firms and its impacts, we first reviewed the current literature regarding the characterization of big data when applied to business scenarios. There is no consensus to date (Gupta & George, 2016).

The discussion of and attempts to define big data processes as they are currently considered goes back to the 1990s; credit for its popularization is often attributed to John Mashey (Diebold, 2012). Most recent definitions list size (i.e., volume) as the first characteristic, because volume is an inherent attribute of big data (e.g., Manyika et al., 2011). However, defining big data in terms of data volume is limiting (Schroeck et al., 2012). Apart from volume, variety and velocity are generally included. The characterization of big data and related processes by words beginning with V has continued. Value is generally considered the fourth characteristic; 42 words beginning with V have been generated by scholars (Shafer, 2017).

As its definition evolves, more characteristics and functions are explored and highlighted (see Table 1). As knowledge about current big data technology itself has reached a saturation point, researchers and practitioners are beginning to focus more on the impacts that big data processes can bring to organizations (Markus, 2015). Some researchers argue that big data is

less a technical term than a marketing term (Power, 2014), and most believe it has become an important asset that facilitates collecting, analyzing, and acting on data from a myriad of sources, including data collected from suppliers, production and operations, sales, customers, and many other internal and external sources (Manyika et al., 2011). For our purposes, we characterize big data and related processes as a technological solution for facilitating the data life cycle and analysis of that data, and as a value creation business process.

Table 1. Representative Big Data Definitions

Sources	Key viewpoints
Boubeta-Puig, Ortiz, & Medina-Bulo (2014)	Big data is "an approach which helps to process this huge amount of data". (p.445)
Chen, Chiang, & Storey (2012)	Big data and big data analytics are used to "describe the data sets and analytical techniques in applications that are so large (from terabytes to exabytes) and complex (from sensor to social media data) that they require advanced and unique data storage, management, analysis, and visualization technologies." (p.1166)
Davenport (2013)	Big data is "a new resolve to apply powerful data-gathering and analysis methods not just to a company's operations but also to its offerings—to embed data smartness into the products and services customers buy." (p.66)
Gunasekaran et al., (2017)	Big data can "help address critical challenges of predictive analytics that refer to data capture, storage, transfer & sharing (i.e. system architecture), and search, analysis, and visualization (i.e. data analytics)."
Lee et al., (2014)	Big data is "a powerful strategic resource for uncovering unforeseen patterns and developing sharper insights about customers, businesses, markets and environments". (p.1)

Liu (2013)	Big data refers to "large, diverse, complex, longitudinal, or distributed data sets generated from instruments, sensors, Internet transactions, email, video, click streams, and all other digital sources available today and in the future". (p.165)
McAfee & Brynjolfsson (2012)	Big data is used to "glean intelligence from data and translate that into business advantage". (p.66)
Manyika et al., (2011)	Big data refers to "datasets whose size is beyond the ability of typical database software tools to capture, store, manage, and analyze." (p. 11)
Wang, Kung, & Byrd (2016)	From the information lifecycle management (ILM) view, big data capability can be defined as "the ability to acquire, store, process and analyze large amount health data in various forms, and deliver meaningful information to users that allows them to discover business values and insights in a timely fashion." (p. 4)

Reviews in Current Literature

There are some reviews of big data related literature. For example, Grover & Kar (2017) analyzed research on big data that appeared in high-quality business management journals and created an industry-specific categorization. Günther et al. (2017) conducted a literature review of research on value impacts from big data and proposed an integrated model of big data value realization. Mikalef et al.'s (2017) review sought to explain the mechanisms through which big data analytics (BDA) contributed to competitive performance. They pointed out that most studies on big data are conceptual or technical; empirical research on big data capability and its impact is limited.

Some scholars' reviews focused in specific areas. For example, Akter & Wamba (2016) reviewed the impact of big data in e-commerce and offered an agenda for future research. Arunachalam, Kumar, & Kawalek (2017) review big data literature in the supply chain area, developing from that a capabilities maturity model. Nguyen et al. (2017) also reviewed big data analytics in the supply chain area, developed from that a classification framework. Sheng, Amankwah-Amoah, & Wang (2017) reviewed big data research in management and business and discussed big data evolution in different business disciplines.

Review of Empirical Studies on Big Data Use Results

There are some empirical studies that have made contributions to the understanding of big data use and its impact on business value creation although the number of empirical studies on the topic are low. Akter et al. (2016) developed a big data analytics capability (BDAC) model and discussed how big data can help firms enhance firm performance (FPER). Gupta & George (2016) identified tangible, technological and human resources, and intangible resources,

including technical skills, managerial skills, a data-driven culture, and intensity of organizational learning, that combine together to form big data capability. Wamba et al. (2017) tested the relationship between big data analytics capabilities and firm performance in presence of the mediation effect of process-oriented dynamic capabilities.

Gunasekaran et al. (2017) investigated how big data and predictive analytics impacted supply chain and organizational performance. Chen, Preston, & Swink (2015) investigated big data analytics use for creating asset productivity and business growth in supply chain management.

Some studies used second-hand data to test big data use impact. For example, Bughin (2016) used a sample of worldwide companies to test how big data impacted firms' productivity performance. Bradlow et al. (2017) discussed big data related models and examined big data use impact in retailing in terms of the dimensions, customers, products, time, location, and channel.

Based on the above discussion, we find that big data use is broad and that expectations and impact from it differ across industries and firms. To better understand results in extant literature of big data impact, we perform a meta-analysis.

Methodology

Meta-Analysis

A meta-analysis is a statistical analysis that integrates results to generalize to a larger population and get a common truth from different views or perspectives. There are some of advantages of this method over other literature review approaches (Gerow et al., 2014). First, because of the wide range of analysis of empirical literature, the precision and accuracy of findings can be improved. Second, it can help identify and explain inconsistency issues across studies.

Sources of Data

The first step in this process was to develop the meta-analysis review protocol. The review process was driven by the research question: *how does the use of big data and its processes drive organizational performance or business value?*

Inclusion Criteria

We identified the inclusion and exclusion criteria for relevant empirical literature. Studies were eligible for inclusion if they were empirical and focused on the topic of big data use and its impact on business value creation. In-progress research, dissertations, and non-English manuscripts would not be included.

We selected electronic databases as our search resource. Specifically, we used the Web of Science, ABI/inform Complete, IEEE Xplore, and ProQuest. The keyword "big data" was the search term; it was allowable in any part of a published manuscript (e.g., title, abstract, main text, etc.). As would be expected with such a broad search term, initial queries resulted in 29220 articles. We then refined the results to business or management journals only, resulting in 3332 studies. Next, we reviewed the articles for our empirical study inclusion criterion. This reduced the count to 69. Unfortunately, of the 69 articles, only 17 focused on the impact of big data processes. Because two articles only using big data context, 15 were kept for final analysis.

Procedure

In addition to the article identification information (e.g., author, year, article-type), we coded some key variables that may help us answer our research question. First, sample characteristics were recorded, including sample size, firm size, industries, big data experience, and data analysis technique. Second, study characteristics were recorded, including big data constructs,

their definitions, the theory or theories used as the research foundation, and the primary results. Last, impact related variables were recorded, including their definitions or measurements, and the R squared statistic.

Results

Sample Characteristics

Sample size, firm size, industries from which data was collected, firms' big data use experience, and whether the data in the analysis was first or second hand was recorded for each article (see Table 2). Sample size and firm size (where reported) vary greatly between studies. A number of industries were represented, indicating that big data process are indeed used across industries. A small number of studies used first hand data to test the relationship between big data use and its impact.

Table 2. Sample Characteristics

Source	Sample size	Firm size (# of employees)		Industries	Big data experience	First-hand or Second-hand data
Akter et al. (2016)	152	<1000, Between 1001 and 2500 Between 2501 and 5000 5000 to 10,000 More than 10,000	23.7% 9.2% 9.9% 8.6% 47.9%	General Information & communication 22.4% Financial & insurance activities 21.7% Manufacturing 10.5% Others 45.4%	N/A	First-hand
Bughin (2016)	714	N/A		General Telecom, high-tech and financial services are the top three industries.	N/A	Second-hand
Chen et al. (2015)	161	N/A		General	N/A	First-hand
Côrte-Real, Oliveira, & Ruivo (2017)	175	<150 50–250 More than 250	8.0% 43.4% 48.5%	General Manufacturing 13.1% Electricity, gas and water supply activities 6.2% Wholesale and retail trade 10.8% Transports and telecommunications 10.2% Financial intermediation 40.5% Others 18.8%	N/A	First-hand
Dubey et al. (2016)	405	< 100 100-249 250-500 > 500	4.94% 8.64% 37.04% 49.38%	Manufacturing Auto components manufacturing 33.33% Heavy Machinery 11.11% Electrical Components 9.14% Infrastructure Sector 7.41%	N/A	First-hand

				Steel Sector 8.64% Chemical 30.37%		
Dubey et al. (2017)	205	<1000 72% More than 1000 28%		<u>Manufacturing</u> Auto component manufacturers 56% Cement manufacturers 5% Chemical products 26% Wood products 13%	N/A	First-hand
Ghasemaghaei, Ebrahimi, & Hassanein (2017)	151	<100 5% 100–1000 42% 1000–5000 28% More than 1000 34%		<u>General</u> Manufacturing 30% Services 48% Financial 15% Utility 7%	N/A	First-hand
Ghasemaghaei, Hassanein, & Turel (2017)	215	N/A		<u>General</u>	N/A	First-hand
Gunasekaran et al. (2017)	205	<1000 72.2% More than 1000 27.8%		<u>General</u> Manufacturing 38.1% Consulting 19.0% E-commerce 6.34% Technology company 36.59%	N/A	First-hand
Gupta & George (2016)	108	<1000, 43% Between 1001 and 2500 13% Between 2501 and 5000 9% 5000 to 10,000 5% More than 10,000 30%		<u>General</u> Computer/Software 16% Manufacturing 4% Finance, Insurance, Real Estate 21% Retail, Wholesale 5% Services 8% Healthcare 9% Others 30%	< 3 years 19% 3–6 years 45% >6 years 36%	First-hand

Kamioka, Hosoya & Tapanainen (2017)	1170	<300 39.7% 500–1000 19.3% More than 1000 41.0%	<u>General</u>	N/A	First-hand
Müller & Jensen (2017)	457	< than 10 21% Between 10 and 49 52% Between 50 and 250 27%	<u>General</u> Production and utilities 26% Trade and transportation 20% Information and communication 10% Others 44%	N/A	First-hand
Ren et al. (2017)	287	N/A	<u>General</u> Information & communication 36.24% Financial & insurance activities 12.54% Manufacturing 14.63% Others 36.59%	N/A	First-hand
Tambe (2014)	1692	N/A	Four-digit industry in database.	N/A	Second-hand
Wamba et al. (2017)	297	N/A	<u>General</u> Information & communication 36.15% Manufacturing 14.19% Financial & insurance activities 12.84% Others 36.82%	N/A	First-hand

Study Characteristics

We identified all conceptually distinct antecedents in terms of big data use. These terms, their definitions, and the statistical results were recorded (see results in Table 3). Although big data capability (BDC) is often considered a high-order construct, it can be conceptualized based on different theories. Some studies in this review conceptualize it as a third-order construct (e.g., Gupta & George, 2016; Wamba et al., 2017) while others use it as a second-order construct (e.g., Ren et al., 2017). There are also differences in BDC focus across studies. For example, Gupta & George (2016) include infrastructure flexibility, management capability, and personnel expertise capability as the second order components. Wamba et al. (2017) identified tangibles, human skills, and intangibles to form the second-order construct. There are few consistencies across studies, even though most focus on BDC as an antecedent to some measure of performance.

Table 2. List of Antecedents, Theory Used, and Selected Results

Constructs	Definition	Theory	β	Positive	Negative	Non-significant
Big data capability (Gupta & George, 2016)	A combination of certain tangible, human, and intangible resources.	RBT (Resources based theory)	0.86 (Market performance)	✓		
			0.67 (Operational performance)	✓		
Big data analytics capabilities (Wamba et al., 2017)	The competence to provide business insights using data management, infrastructure (technology) and personnel capability to transform business into a competitive force.	RBV (Resource-based view)	0.56 (Firm performance)	✓		
			0.84 (Process-oriented dynamic capabilities)	✓		
Big data analytics capabilities (Akter et al., 2016)	The competence to provide business insights using data management, infrastructure (technology) and talent personnel) capability to transform business into a competitive force.	RBT (Resources based theory)	0.709 (Firm performance)	✓		
Big data & predictive analytics capability (Dubey et al., 2017)	A capability based on existing environmental conditions which is essential for an organization, including technical skill, managerial skills, data driven decision making culture, and organizational learning.	DCV (Dynamic capability view)	0.726 (Social performance)	✓		
			0.854 (Environmental performance)	✓		

BDA endogenous knowledge (Côrte-Real, Oliveira, & Ruivo, 2017)	One type of knowledge assets.	KBV (Knowledge based view) ; DCV (Dynamic capability view)	0.155 (Agility)	✓		
BDA exogenous knowledge (Côrte-Real, Oliveira, & Ruivo, 2017)	One type of knowledge assets.		0.238 (Agility)	✓		
BDA knowledge sharing (Côrte-Real, Oliveira, & Ruivo, 2017)	The extent to which a firm shares insights and know-how about its business context with its partners.		0.344 (Process-level performance)	✓		
Big data and predictive analytics assimilation (Gunasekaran et al., 2017)	A capability that impacts performance.	RBV (Resource-based view)	0.45 (Supply chain performance)	✓		
			0.17 (Organizational performance)			
Big data labor investment (Bughin, 2016)	A large enough pool of complementary talents for investment in big data projects.	N/A	0.012 (Corporate performance)	✓		
Big data capital investment (Bughin, 2016)	Big data related machinery and IT.	N/A	0.021(Corporate performance)	✓		
Big data usage (Chen et al., 2015)	Firms implement big data analytics in areas, sourcing	DCV (Dynamic capability view)	0.291(Asset productivity)	✓		

				✓		
	analysis, purchasing spend analytics, CRM/customer/patient analysis, network design/optimization, warehouse operations improvements, process/equipment monitoring, production run optimization, logistics improvements, forecasting/demand management, and inventory optimization		0.303(Business growth)	✓		
Organized big data analytics (Kamioka, Hosoya & Tapanainen, 2017)	The degree that big data analytics is organized as a consequence of having a high big data analytics capabilities.	RBV (Resource-based view)	0.32(Performance of big data analytics)	✓		
			0.39 (Competitive advantage)	✓		
BDA system quality (Ren et al., 2017)	Include systems reliability, system adaptability, system integration, system accessibility, system response time and system privacy.	RBV (Resource-based view)	0.61 (BDA business value)	✓		
			0.49 (Firm performance)	✓		
BDA information quality (Ren et al., 2017)	Completeness, accuracy, format and currency of information produced by BDA.	RBV (Resource-based view)	0.29 (BDA business value)	✓		
			0.15 (Firm performance)	✓		
The application of Big Data (Müller & Jensen, 2017)	Include six elements: data, enterprise, leader, target, technology, and analysis.	N/A	N/A(Business value creation)	✓		

Big data investment (Tambe, 2014)	Capital	Complementarities theory	0.308(Value added)	✓		
Data analytics competency (Ghasemaghaei, Ebrahimi, & Hassanein, 2017)	A firm's ability to deploy and combine data analytics resources for rigorous and action-oriented analyses of data, including data quality, bigness of data, analytical skills, domain knowledge, and tools sophistication.	Resource-Based View (RBV) & Huber's theory (1990) (Theory of effects of advanced IT on decision making)	0.883 (Decision making performance)	✓		
Data analytics use (Ghasemaghaei, Hassanein, & Turel, 2017)	The extent and frequency of employing such tools within organizations.	DCV (Dynamic capability view)	-0.108 (Firm Agility)			✓

Outcome Characteristics

There are many dimensions that can be used to measure the impact of big data processes in an organization. Among these are competitive advantage, productivity enhancement, profitability improvement, and cost reduction (Devaraj & Kohli, 2003). Firm performance is the construct that scholars use most often to measure big data use results. Traditionally, there are three over-arching types of performance to measure IT performance, operational excellence, productivity, and customer benefits (Tallon, 2007). These there demimention are still commonly used in current big data use outcome literature.

While most of the articles in this review indicate positive effects on performance, there are some differences among the studies. For example, R^2 in terms of market performance in Wamba et al.'s study (2017) is higher than in Gupta & George's (2016) study. Of course, the structure of the study (such as Wamba et al.'s use of second-order constructs) or the different operationalization of big data processes account for some of the difference. Either way, there is consistency in the findings that market performance did benefit from big data capabilities.

In addition to direct effects on firm performance outcomes, big data use can also improve organizational capability. For example, Wamba et al. (2017) found that big data use positively affects process-oriented dynamic capabilities, and in turn on firm performance. Côrte-Real, Oliveira, & Ruivo (2017) showed that big data helps improve organizational agility. Extant literature, although sparse, does indicate that big data process use in an organization will lead to enhancements within the organization.

Table 3. Outcome Characteristics

Constructs	Definition or Measurements	R^2
Market performance (Gupta & George, 2016)	✓ Entering new markets more quickly than competitors. ✓ Introducing new products or services into the market faster than competitors. ✓ Success rate of new products or services being higher than competitors. ✓ Market share exceeding that of competitors.	46.2%
Operational Performance (Gupta & George, 2016)	✓ Productivity exceeding that of competitors. ✓ Profit exceeding that of competitors. ✓ Return on investment (ROI) exceeding that of competitors. ✓ Revenue exceeding that of competitors.	74.4%
Process-oriented Dynamic Capabilities (Wamba et al., 2017)	The extent to which a firm can develop or acquire required competences to change its existing business processes in a more robust way than its competitors in terms of coordination, integration, cost reduction, and business intelligence and learning related to big data analytics projects. ✓ Better than competitors in connecting (e.g., communication and information sharing) parties within a business process. ✓ Better than competitors in reducing cost within a business process. ✓ Better than competitors in bringing complex analytical methods to bear on a business process. ✓ Better than competitors in bringing detailed information into a business process.	70%
Firm Performance (Wamba et al., 2017)	The firm's ability to gain and retain customers, and to improve sales, profitability, and return on investment (ROI), including financial performance and market performance. Financial performance ✓ Better than competitors in customer retention. ✓ Better than competitors in sales growth. ✓ Better than competitors in profitability.	65% 90%

	✓ Better than competitors in return on investment. ✓ Better than competitors in overall financial performance. Market performance ✓ Entering new markets more quickly than competitors ✓ Introducing new products or services to the market faster than competitors. ✓ Success rate of new products or services higher than competitors. ✓ Market share exceeding that of competitors.	89%
Firm Performance (Akter et al., 2016)	A firm's competence to change existing business processes better than competitors do in terms of coordination/integration, cost reduction, and business intelligence/learning. ✓ Better than competitors in customer retention. ✓ Better than competitors in sales growth. ✓ Better than competitors in profitability. ✓ Better than competitors in return on investment. ✓ Better than competitors in overall financial performance.	50.3%
Social performance (Dubey et al., 2017)	✓ Total employment. ✓ Employee per enterprise. ✓ Average gross wages per employee. ✓ Male vs female full time employment.	50.8%
Environmental performance (Dubey et al., 2017)	✓ Reduction of air emission. ✓ Reduction of waste water. ✓ Reduction of solid wastes. ✓ Decrease in consumption of hazardous/harmful materials. ✓ Improve an enterprise environmental situation.	72.1%
Environmental performance (Dubey et al., 2016)	✓ Environmental technology ✓ Recycling efficiency ✓ Eco packaging ✓ Level of process management which includes pollution control, waste emissions, carbon footprint etc.	52%

Social performance (Dubey et al., 2016)	✓ Management commitment ✓ Customer satisfaction ✓ Employee development	45%
Economic performance (Dubey et al., 2016)	✓ Environmental cost ✓ Supply chain cost ✓ Return on asset	48%
Process-level performance (Côrte-Real, Oliveira, & Ruivo, 2017)	✓ Production and operations: improve throughout, boost labor productivity, improve flexibility and equipment utilization, and streamline operations. ✓ Product and service enhancement: embed IT in products, increase pace of development/R&D, monitor design cost, improve quality, support innovation. ✓ Customer relations: respond to customer needs, provide after-sales service and support, improve distribution, create customer loyalty	57.8%
Organizational agility (Côrte-Real, Oliveira, & Ruivo, 2017)	Capacity of an organization to efficiently and effectively redeploy/redirect its resources to value creating and value protecting (and capturing) higher-yield activities as internal and external circumstances warrant. ✓ React to new product or service launches by competitors. ✓ Expand into new regional or international markets. ✓ Change (i.e., expand or reduce) the variety of products/services available for sale. ✓ Adopt new technologies to produce better, faster, and cheaper products and services	61.8%

Supply chain performance (Gunasekaran et al., 2017)	✓ Organization has full visibility of our supply chain. ✓ Organization appropriately manages supply chain risk ✓ Organization's primary supply chain has the ability to minimize total product cost to final customers. ✓ Organization's primary supply chain has the ability to deliver product precisely on-time delivery to final customers. ✓ Organization's primary supply chain has the ability to deliver zero-defect products to final customers. ✓ Organization's primary supply chain has the ability to minimize all types of waste throughout the supply chain. ✓ Organization's primary supply chain has the ability to deliver right-sized lot sizes and shipping case sizes to final customers. ✓ Organization's primary supply chain has the ability to eliminate late, damaged and incomplete orders to final customers. ✓ Organization has the ability to minimize channel safety stock throughout the supply chain. ✓ Organization's primary supply chain has the ability to deliver value-added services to final customers. ✓ Organization's supply chain has the ability to respond faster than competitors to changing environments.	N/A
Organizational performance (Gunasekaran et al., 2017)	✓ Return on investment ✓ Profit ✓ Return on sales ✓ Market share growth ✓ Sales volume growth ✓ Sales growth	N/A
Corporate performance (Bughin, 2016)	Better productivity than peers.	N/A

Asset productivity (Chen et al., 2015)	A primary measure used to assess supply chain performance, describing the extent to which a business productively uses both current assets (e.g., cash, inventory) and fixed assets (e.g., plant, property, and equipment Cash-to-cash cycle time (receivables + inventory–payables). ✓ Inventory turnover (sales/inventory) ✓ Asset turnover (sales/total assets) ✓ Return on asset (ROA)	14.9%
Business growth (Chen et al., 2015)	A function of the capability of creating a series of temporary advantages. ✓ Average year on year sales growth ✓ Market expansion ✓ Market share growth	16.8%
Performance of big data analytics (Kamioka, Hosoya & Tapanainen, 2017)	✓ Satisfaction with the variety of data the firm is able to collect ✓ Satisfaction with time required to collect data ✓ Satisfaction with time required to analyze data	15%
Competitive advantage (Kamioka, Hosoya & Tapanainen, 2017)	✓ Big data utilization contributing to present competitive advantage.	28%
BDA business value (Ren et al., 2017)	The transactional, strategic and transformational value of BDA. Transactional value includes cost reductions. Strategic value refers to the degree of perceived benefits to the organization at a strategic level, e.g. competitive advantage; and, finally, transformational value refers to the degree of perceived changes in the structure and capacity of a firm as a result of BDA, which serve as a catalyst for future benefit.	74%

Firm performance (Ren et al., 2017)	The firm's ability to gain and retain customers; and to improve sales, profitability and return on investment (ROI), including financial performance and market performance. <u>Financial performance</u> ✓ Customer retention ✓ Sales growth ✓ Profitability <u>Market performance</u>. ✓ Entering new markets more quickly than competitors. ✓ Introducing new products or services into the market faster than competitors. ✓ Success rate of new products or services being higher than competitors. ✓ Market share exceeding that of competitors.	76%
Value creation (Müller & Jensen, 2017)	N/A	N/A
Decision making performance (Ghasemaghaei, Ebrahimi, & Hassanein, 2017)	The users' evaluations of decision quality and efficiency in their decision making process. <u>Decision quality:</u> decision outcomes are accurate, correct, precise, flawless, error-free, and reliable <u>Decision Efficiency</u> ✓ the time to arrive at decisions ✓ the speed of arriving at decisions	0.779
Firm agility (Ghasemaghaei, Hassanein, & Turel, 2017)	A dynamic capability within firms to identify and effectively respond to threats and opportunities with speed, including operational adjustment agility and market capitalizing agility.	0.472

Propositions

After reviewing the above, we propose the following:

Sample Size

Proposition: Sample size is not a significant indicator of the outcome of big data processes on the organization.

Industry Type

Proposition: Type of industry is an indicator of the intensity of the outcome of big data processes on the organization.

Operationalization of Big Data Processes

Proposition: Positive outcomes to the organization will be indicated regardless of the type of big data use operationalized (e.g., data life cycle measures, analysis types)

Operationalization of Organizational Impact

Proposition: Positive outcomes to the organization will be indicated regardless of the type of outcome measure (e.g., market performance, responsiveness, etc.)

Discussion

Implications for Theory

The theories that are used most to develop big data analytics capability are the resource based theory (RBT), dynamic capability view (DCV), and the knowledge based view (KBV). This study shows that, because of the flexibility of both big data processes and expected impacts, there is no one theory that is superior to another when investigating these relationships. The

resources based view seeks to explain how firms win competitive advantage or create business

value using various resources; big data capability is often formed by a analyzing a mix of

tangible and intangible assets. However, simply having the resource in the organization is not

sufficient to affect impact (Grant, 1991); big data capability is valuable only if it is strategically

leveraged for a particular purpose (expand market share, improve organizational response time,

etc.). Further, these relationships do not tend to be simple ones. There is evidence in the extant

empirical literature that both mediators and moderators exist. However, from a dynamic

capability view, findings of the impact of big data capabilities are more direct when investigating

competitive advantage or business value. While all of the theories represented here were

sufficient to ground the research, it appears that scholars may leverage different theories when

looking to explain simple or complex relationships between big data capabilities and the impacts

it brings.

Implications for Practice

This study offers a better understanding of big data use impacts in practice and help firms

understand how to generate firm performance, acquire business value, and gain competitive

advantage. A review such as this provides a bigger picture of the types of capabilities and the

types of impacts that may be expected than any one research study can alone. Looking at the

articles here, we find that organizational capabilities may mediate or moderate the relationship

between big data capability and outcomes; understanding of when this is true and ultimately how

to best manipulate them will allow organizations to leverage what is available into the best

outcome possible. For example, process-oriented dynamic capability was identified and

confirmed as a mediator between big data capability and firm performance. In this case, a firm

should not only consider its capabilities and the impact it hopes to gain, but also how is processes

may be best leveraged to maximize the gain. Analytics capability-business strategy alignment is a moderator between big data capability and firm performance.   Knowing about this complex relationship should help managers strive toward the alignment that is required to best maximize the impacts of big data capability.

Future Research

Based on the above results, we integrate the theories with the findings and develop a general big data use impacts framework (see Figure 1).
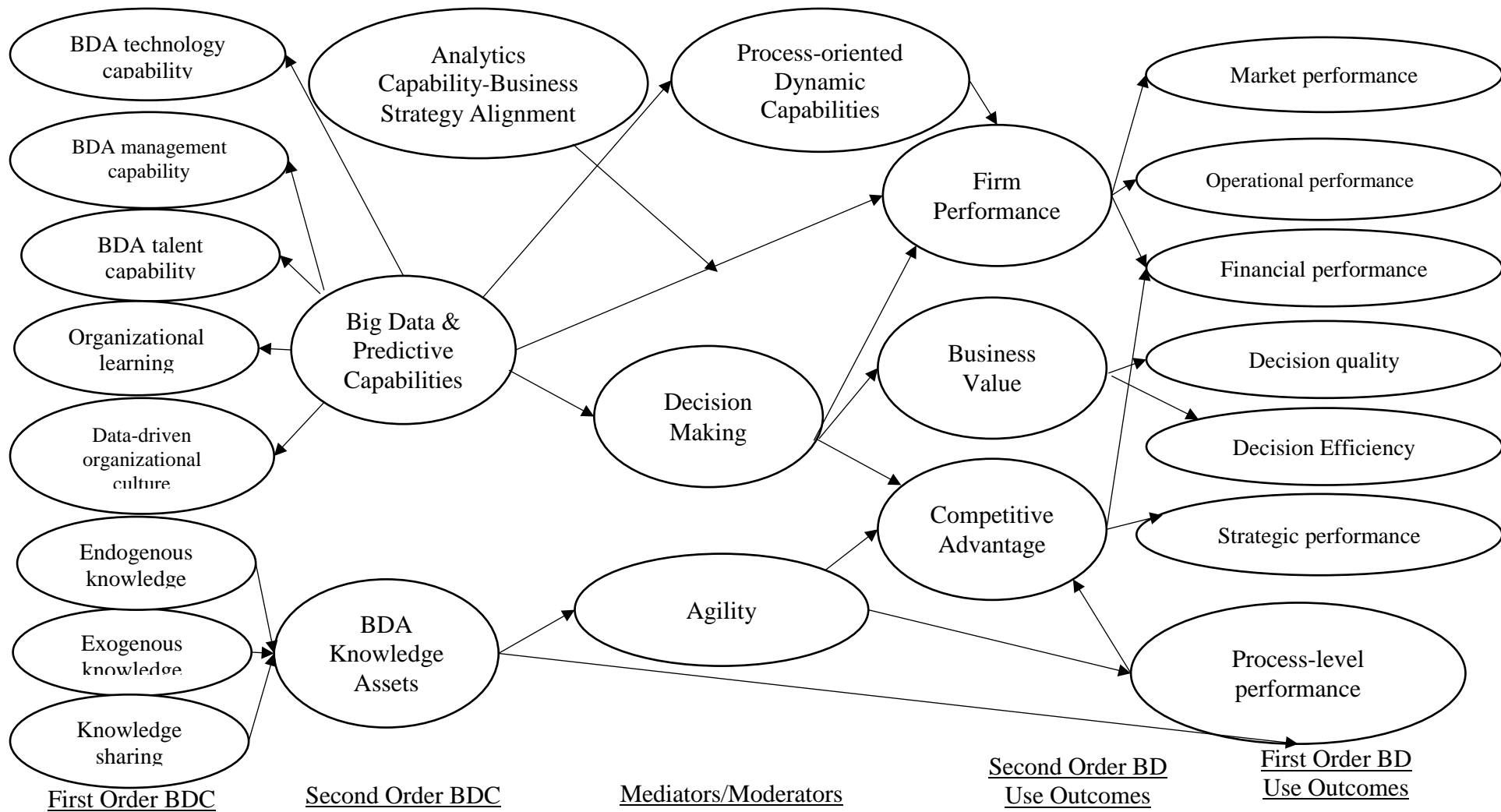
Figure 1Big Data Use Impacts Framework

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From the proposed framework, this study provides directions and suggestions for researchers in the big data capabilities domain. The potential areas may include:

1. The development of big data capabilities

2. The identification of organizational capabilities that can connect big data capability with big data use impact

3. Big data use in other industries

4. Big data use impact in other aspects

Conclusion

We reviewed extant literature that empirically examined the relationship between big data use and business value creation; from there, we developed a big data use effects framework. As extant research increases, the impact of big data is becoming more evident. Our framework will allow future researchers to focus on specific areas from different perspectives as desired. This will allow, over time, a comprehensive look at what appears to be a flexible, yet complex area from which much knowledge, both theoretical and practical, can still be gained.

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ESSAY 2: ORGANIZATIONAL READINESS FOR CHANGE AND INTENTION TO ADOPT BIG DATA

Introduction

The current business environment is becoming more volatile. Internal and external factors, such as those presented by employees, customers and competitors, aggravate the stresses of operating in increasingly competitive environments. Firms face increasing challenges making effective strategic decisions and coping with the market's unprecedented turbulence. In a dynamic, rugged, and competitive landscape, internal operations and the external environment of the firm exacerbate uncertainty (Tanriverdi, Rai, & Venkatraman, 2010), making prediction difficult. Effective use of IT to build competitive advantage in a turbulent environment has long been a challenge for scholars and practitioners (Pavlou & El Sawy, 2006). Big data offers firms new opportunities to develop competitive advantage. Big data technology facilitates decisions that make business processes more agile in a turbulent environment; this is also likely to facilitate organizational change (Demirkan & Delen, 2013).

Many studies have discussed how information technology (IT) creates value and improves firms' performance (e.g., Byrd & Marshall, 1997; Byrd & Turner, 2001). IT is integral to organizational change (Bergeron, Raymond, & Rivard, 2004). In turbulent market environments, firms are more willing to adopt state-of-the-art information technologies to enhance competitive advantage and work through resultant changes than when competitive pressures are low (Low, Chen, & Wu, 2011). Organizations that fail to make timely changes are likely to lose market share. Currently, firms are striving to achieve a competitive advantage

through implementation of big data technology innovation. Adopting business analytics related applications has become a top priority to many firms (LaValle et al., 2011). IDC forecasts that the big data technology and services market, including infrastructure, software, and the services submarkets, will be increasing at a compounded annual growth rate (CAGR) of 23.1% through 2019 and that annual spending will reach $48.6 billion in 2019 (IDC, 2015). A recent report assessing big data adoption by the International Institute for Analytics found that, since 2014, an increasing number of executives have recognized the business benefits realized through analytics and have implemented big data at a faster rate than previous adoptions (IIA, 2016).

Big data is complex to use. In addition to data sourcing and technology challenges, managerial and cultural factors are prominent barriers to a successful adoption (LaValle et al., 2011). Among these factors, organizational readiness for change is a critical precursor to embracing new innovations. Readiness refers to organizational members' attitudes, beliefs and intentions (Armenakis, Harris, & Mossholder, 1993). Organizational readiness for change refers to "the extent to which organizational members are psychologically and behaviorally prepared to implement organizational change" (Weiner et al., 2008, p. 381).

Employee attitudes toward technology use are key to the success of new technology innovation. IT can positively affect firm performance if it is accepted and used by the end users as intended (Venkatesh & Bala, 2008; Venkatesh et al., 2008). Readiness is one critical factor involved in employees' initial support for change initiatives (Armenakis, Harris, & Mossholder, 1993). Past research has suggested that organizational readiness can influence organizational information technology adoption behaviors (Armenakis, Harris, & Mossholder, 1993). Big data use has a close relationship with organizational change readiness (Chen, Preston, & Swink, 2015; Shah, Irani, & Sharif, 2017). The processes involved while implementing, integrating, and using

big data should be easy for end-users to understand and accept so that the benefits can be fully gained. A successful adoption requires active interaction between big data implementors and end-users.

Market turbulence, as one of the typical external environmental factors, can produce organizational pressures that can speed up or slow down an organization's determination to change. Increasing turbulence in the business environment drives firms to find new approaches and ways to gain competitive advantage. It is generally acknowledged that rapid market change can have a destructive impact on the existing relationship between firms' adoption of innovations and its antecedents (Weiss & Heide, 1993). Market demand is one of the organizational drivers necessary to implement new innovations. Big data adoption and the effect of its use are moderated by dynamic markets (Chen, Preston, & Swink, 2015).

However, most industries are still in an early stage of big data adoption or implementation. Many executives are hesitant to adopt big data because of the paucity of knowledge of big data processes and little understanding of how to generate insights from big data (Wamba et al., 2015). There is still a need to investigate the relationship between internal and external factors and organizational intention to adopt big data. It is our purpose to test the relationship between organizational readiness for change and big data adoption decision making in a turbulent market.

The remainder of this article is structured as follows. We first provide a literature review summarizing the salient points of open-systems theory and the main constructs, readiness for change, market turbulence, and intention to adopt. Next, we develop the hypotheses that discuss the relationships among constructs. Following this, we describe the research methodology, and

then we explain the data analysis and present the results. We close with a discussion as to how our research contributes to both theory and practice.

Literature Review

Theoretical Foundation

Many models and theories have been developed to discuss new information technology acceptance. Some classical theories or models are the theory of reasoned action (Fishbein & Ajzen, 1975), the technology acceptance model (Davis, 1989), the theory of planned behavior (Ajzen, 1991), the innovation diffusion theory (Rogers, 2003), and the social cognitive theory (Compeau & Higgins, 1995). Some scholars believe that new technology adoption happens when various factors come together. To attempt to explain this, researchers combine theories or models to emphasize the effect of multiple factors. For example, Taylor & Todd (1995) combine the technology acceptance model and the theory of planned behavior to investigate the use of new technology. By integrating existing study results into one unified model, Venkatesh et al. (2003) developed the Unified Theory of Acceptance and Use of Technology.

The theoretical foundation of this study is open-systems theory. Evaluating internal and external environments is of great importance for adoption decision making. We contend that adopting big data is a change to firms. A firm's intention to adopt big data indicates its determination to make a change. Unlike traditional theories that view organizations as being isolated from the outside world, open-systems theory not only considers internal elements but also includes environmental factors to explain organizational changes (Katz & Kahn, 1978). It can well explain how organizations are involved in an environment (Mele, Pels, & Polese, 2010). Grounded in this theory, many scholars have argued the openness of a firm and how it responds

to environmental threats. For example, Wanberg & Banas (2000) investigated the predictors and outcomes of organizational members' openness to a series of work-related changes. With openness, employees are more likely to embrace organizational change (Armenakis, Harris, & Mossholder, 1993). Through the lens of this theory, organizational change happens in an input-output process in which internal elements such as people, capital and information interact with the external and internal environments.

We argue that internal enablers coupled with external pressures drive organizational intention to adopt big data. Change readiness is a "cognitive precursor to the behaviors of either resistance to, or support for, a change effort" (Armenakis, Harris, & Mossholder, 1993, p. 681). It can play a role in reducing the failure rate when organizations make a change. Thus, organizations must create a change-positive environment before implementing a change. Readiness for change is an important organizational characteristic and also has an impact on information technology adoption (Petter, delone, & McLean, 2013). Organizational readiness for change is especially important in a turbulent business environment because firms in such an environment usually face a higher competition pressure and have a higher motivation to change; this is often accomplished by adopting and taking advantage of new information technology (Straub et al., 1997). As a multi-level construct, readiness for change can be used to measure individuals' attitude or willingness to accept and embrace new changes. Appropriateness, management support, change self-efficacy, and personal valence can be used to measure organizational readiness for change (Holt et al., 2007a).

Readiness for Change

Based on a systematic review of the readiness literature, Holt et al. (2007b) defined readiness for change as "A comprehensive attitude that is influenced simultaneously by the

content (i.e., what is being changed), the process (i.e., how the change is being implemented), the context (i.e., circumstances under which the change is occurring), and the individuals (i.e., characteristics of those being asked to change) involved and collectively reflects the extent to which an individual or a collection of individuals is cognitively and emotionally inclined to accept, embrace, and adopt a particular plan to purposefully alter the status quo" (Holt et al., 2007b, p. 326).

Many studies have concluded that organizational members' attitudes and beliefs can influence the decision to adopt new information technology (e.g. Keen, 1981). Holt et al. (2007a) argued that readiness for change is influenced by four factors, including change content, change process, internal context, and individual characteristics. Thus, they suggested readiness for change should be defined to reflect the extent to which organizational members collectively are cognitively inclined to accept and adopt a new innovation. This can be measured by aggregating individuals' appraisals or individuals' assessments of collective capabilities when the outcome is the sum of individual performance (Bandura, 2000; Klein, 2000; Weiner, 2008).

Appropriateness

Appropriateness means that the prospective change is advantageous for the organization (Holt et al., 2007a). This includes two aspects, discrepancy and organizational valence. Discrepancy represents organizational members' perceptions that the change is needed. An organizational change process occurs over a period of time. The change will not occur unless organization members believe the situation is necessary (Kotter, 1996). Organizational valence represents organizational members' perception that the change will be beneficial to the organization. Organization members' awareness of the need to embrace a new innovation is critical to a successful adoption. When firms adopt a new innovation, employees are likely to

question whether it is the right one to implement. To ensure a successful change, firms need to give employees a change signal in dramatic and insistent terms to encourage those employees to accept that the adoption solution is appropriate.

Management support

Management support or senior leadership support refers to "the extent to which one feels that the organization's leadership and management are or are not committed to and support or do not support implementation of the prospective change" (Holt et al., 2007a p.239). Higher management support indicates that executives are willing to allocate resources and encourage the initiative adoption (Holt et al., 2007a). This suggests that organization leaders are committed to the successful implementation and institutionalization of the change (Armenakis & Bedeian, 1999). Management support is a critical factor in the adoption of new technology innovations. The fastest rate of adoption of an innovation usually comes from authority decisions (Rogers, 2003). Support from top management can provide strategic direction, authority, and resources during the adoption of big data. Support from top managers can also encourage other organizational members to move positively and act accordingly.

Change self-efficacy

Change self-efficacy refers to "the extent to which one feels that he or she has or does not have the skills and is or is not able to execute the tasks and activities that are associated with the implementation of the prospective change" (Holt et al., 2007a, p.238). Readiness for change is not only a state of being willing to take action for change, but also a state of being able to make the change happen (Weiner, 2009). Organization members' cognitive appraisal of implementation capability is a critical factor to ensure the success of a new change. High change self-efficacy means that organization members have appropriate experience and skill to easily

handle the changes when adopting new innovations (Holt et al., 2007a). Change self-efficacy can

be used to measure organization members' perception of difficulty towards the change. Change

self-efficacy is very important for employees because the change is likely to require them to

acquire additional knowledge and skills for employees (Avey, Wernsing, & Luthans, 2008).

Personal valence

Valence is the extent to which the change is perceived as beneficial or detrimental (Oreg,

2006). Personal valence is "the extent to which one feels that he or she will or will not benefit

from the implementation of the prospective change" (Holt et al., 2007a, p. 238). Personal valence

is a cost-benefit appraisal process in which employees evaluate the significance of the proposed

change for their own wellbeing. These benefits may be extrinsic or intrinsic for employees. An

employee's perceptions of the outcome of change can strongly influence whether they will

support a decision. To some extent, personal valence is the direct factor that motivates

employees to accept or resist a change. A potential loss from a change can cause resistance.

Firms must play an active role in lowering the resistance behaviors from employees. This factor,

along with the other three, is critical for a successful adoption.

Market Turbulence

Market turbulence is often caused by changes in customers' product preferences,

demand, and needs (Hult, Ketchen, & Arrfelt, 2007; Jaworski & Kohli, 1993). It has been

defined in different ways but is usually used to describe the general conditions of uncertainty or

unpredictability resulting from changes in the market (Pavlou & El Sawy, 2006). These changes

may arise from market demands, consumer preferences, and intense competition (Pavlou & El

Sawy, 2006).

Early scholars focused on customer demands and preferences (e.g., Slater & Narver, 1994). In addition to capturing the dynamism in the customer base and needs, later scholars included more components to reflect market uncertainty. Hult, Hurley, & Knight (2004) have argued that market turbulence also reflects rapidly changing buyer preferences. Some other factors, such as an unstable economic climate and new inventions of technology are also drivers of market turbulence.

Market turbulence makes it difficult for firms to accurately predict the future of market preferences and the state of the competitive environment. Firms across industries frequently adopt new innovations in response to the turbulence of markets. The adoption of new technology relies on the characteristics of the marketing environment in which the firm operates. However, because of the dynamic nature of market, the effect of readiness for change may differ under different market conditions. We contend that big data adoption decision making is influenced by market turbulence, which may play a moderating role between organizational readiness for change and adoption intention.

Hypotheses Development

The Effect of Appropriateness on Firms' Intention to Adopt Big Data

If employees believe an impending change is correct for the organization, they are likely to support it. Lack of clarity regarding the need and urgency for the change may make employees resistant to the change. Big data as a new innovation bring opportunities for firms. The advantage should be properly conveyed to employees. They must understand that the current state is not satisfactory and the adoption of big data processes is necessary to reach a state that is

more desirable for the organization's growth. Resistance from employees will be reduced as the perceived need for change increases. Thus, we hypothesize that,

Hypothesis 1: Perceived appropriateness will positively affect a firm's intention to adopt big data.

The Effect of Management Support on Firms' Intention to Adopt Big Data

The fastest rate of adoption of an innovation is often a result of authority decisions (Rogers, 2003). Senior management is expected to set strategic guidelines for an organization from a long-term point of view. Top managers with higher motivation to accept new innovations can exert more influence on the firm's adoption decision. Management support helps create positive environments, ensures adequate resources for adopting the innovation, and coordinates the diffusion process for accepting new innovations among organization members.

Management support can also determine the allocation of resources that will be used to support innovation implementation. If executives have stronger competence and confidence to make a change, they can exert more influence on firms' adoption of big data. Additionally, employees will look to managers for cues if uncertainty of a change is present (Armenakis & Bedeian, 1999). If managers advocate for the change, resistance from employees will drop. There is substantial theoretical and empirical evidence that supports the relationship between top management support and intention to adopt new technology (e.g., Martins, Oliveira, & Thomas, 2016). Thus, we hypothesize that,

Hypothesis 2: Management support will positively affect a firm's intention to adopt big data.

The Effect of Change Self-Efficacy on Firms' Intention to Adopt Big Data

Weiner (2009) pointed out that task demands, resource availability, and situational factors determine organizational members' judgement of implementation capacity. Organizational members gain confidence in change implementation when these factors are considered to be non-issues. High self-efficacy indicates that an individual believes that the goal of the task is explicit, sufficient resources are available, and other situational factors are suitable for facilitating change. High self-efficacy may help employees cope with the pressures associated with change, making the change seem easy to address, and may help employees build confidence which in turn will lean to embracing change. Implementation of big data often requires new knowledge and skills; this may be challenging for some employees. Those who have some related knowledge will have higher self-efficacy to weather the change and are more likely to favor the adoption decision whereas employees without related knowledge are more likely to reject or resist the changes. Thus, we hypothesize that,

> **Hypothesis 3: Change self-efficacy among organizational employees will positively affect a firm's intention to adopt big data.**

The Effect of Personal Valence on Firms' Intention to Adopt Big Data

Personal valence can affect many organizational operations. In terms of new innovation adoption, personal valence is associated with employees' perceived benefits when making the change. Compared with the benefits that an organization will realize from the adoption of big data, employees are more concerned about whether they will individually benefit from the change. Thus, employees' personal valence should be a part of big data adoption decision. If organizational members do not see personal benefit, they are likely to hinder the change process. If consequences are seen as potentially harmful, they are not likely to support and may even

sabotage or reject the change. However, if the change is viewed as a personal opportunity, organizational members will be more willing to embrace the effort. Thus, we hypothesize that,

Hypothesis 4: Personal valence of organizational members will positively affect a firm's intention to adopt big data.

The Moderating Effect of Market Turbulence on Firms' Intention to Adopt Big Data

In a turbulent environment, it will be difficult to adopt a new technology because of many external factors that may be occurring simultaneously. Firms will undertake different IT adoption strategies under different market conditions. Environmental scanning is a necessary precursor to an adoption decision. Much research has suggested that new technology innovation adoption decisions correspond to increasingly competitive environments because turbulent markets require more advanced IT competence to address market pressures (Grant, 1996). In an uncertain environment where customer preferences are constantly changing, firms across industries will seek new innovations and use them to help mediate market turbulence (Rigby& Zook, 2002).

Big data technologies are an innovation that are frequently adopted when market turbulence is increasing, such as when customers are becoming more demanding and require increasingly higher levels of service. When market turbulence is low, organizations do not seek to embrace new technologies. As turbulence increases, however, firms turn to the insights provided by big data to support business processes and operations management. The higher the rate of market turbulence, the greater the need to use big data in the organization to exploit more valuable business opportunities that turbulent environments present (Sambamurthy, Bharadwaj, & Grover, 2003).

In a stable market, firms are likely to reserve their slack resources (financial, human, and technology resources) and maintain the status quo rather than invest in new technology (Meyer, Brooks, & Goes, 1990). As turbulence increases, firms may seek to adopt new technologies such as big data but these adoptions may be more susceptible to issues regarding readiness to change. The perceived urgency of the need for change may hinder the process of management carefully explaining the need for, and benefits from, the change. The relative newness of big data and its technologies may exacerbate the effect of, for example, self-efficacy and personal valence. The effect of readiness for change on the intention to adopt big data is greater under high market turbulence than under low market turbulence. Thus, we hypothesize that,

Hypothesis 5a: The effect of appropriateness on intention to adopt big data is greater under high market turbulence than under low market turbulence.

Hypothesis 5b: The effect of management support on intention to adopt big data is greater under high market turbulence than under low market turbulence.

Hypothesis 5c: The effect of change self-efficacy on intention to adopt big data is greater under high market turbulence than under low market turbulence.

Hypothesis 5d: The effect of personal valence on intention to adopt big data is greater under high market turbulence than under low market turbulence.

Based on the above discussion, the conceptual framework is developed (see Figure 1).
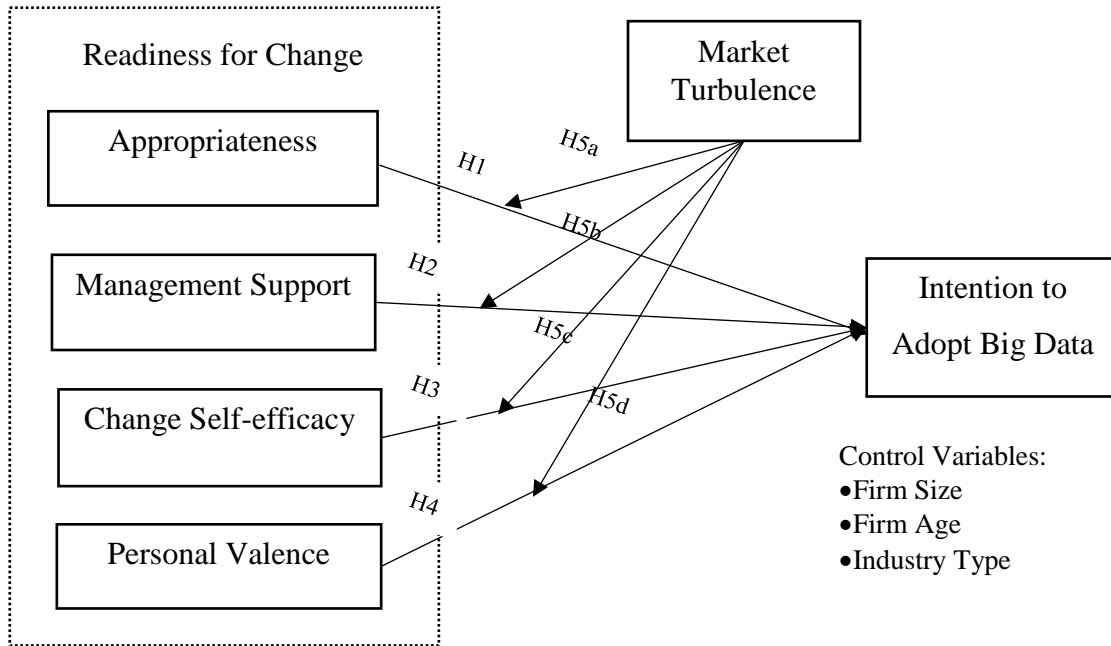
Figure 1. Conceptual Framework

Methodology

Sampling Frame

The researchers employed the survey method. Before distributing the questionnaires, a pilot test was conducted to check the quality of the survey by using a sample of 15 IT managers in Zhongguancun Science Park, the first high-tech park in Beijing, China. The results and their feedback helped us identify poor performing items, avoid culture-sensitive concepts, improve the back-translation accuracy and reword a few items that were not clear. As the respondents are experts in this area, their assessment also increased the content validity.

We collected primary data from five top MBA, EMBA, and Computer Engineering Master programs in the east of China. There is increasing recognition that China is in a big data adoption phase (Reed & Dongarra, 2015). Its quick development of e-commerce and online markets attracts scholars to collect data regarding information technology implementation

(Wamba et al., 2017). Because of a dynamic transitional economy and a turbulent market environment, data from China can be used to test our hypotheses. The respondents were responsible for or significantly involved in decision-making in business activities and had knowledge of big data practice in their firms. The firms were non-adopters of big data related applications. To qualify for sample, target individuals were required to be at least a middle or upper-level manager in his or her company. Although students at the time of the study while taking on campus classes on weekends, all respondents had work experience and were full-time employees.

In total, 350 questionnaires were distributed to potential participants and 229 were returned, resulting in a 65.4% response rate. Of the returned questionnaires, after deleting responses that were unusable, 197 were maintained for data analysis. Of the respondents, 35.5% were top managers and 64.5% middle managers. Table 1 shows the profile of the respondents.

Table 1. Profile of Respondents (n=197)

Characteristics	Category	Number	%
Firm size	1-500	57	28.9
	500-1000	44	22.3
(number of employees)	1000-2000	34	17.3
	Over 2000	62	31.5
Total annual revenue	0-100	57	28.9
	1000-1000	62	31.5
(USD, millions)	10000-10000	48	24.4
	Over 10000	30	15.2
Firm age	Less than 10 years	44	22.3
	11-20 years	71	36.0
	21-40 years	43	21.8
	Over 40 years	39	19.8
Industry	Manufacturing	72	36.5
	Service-oriented	125	63.5
	Top manager (CEO, CTO etc.)	70	35.5

Respondent job title	Middle manager	127	64.5
Working experience	Less than 3 years	12	6.1
	3-10 years	109	55.3
(years)	Over 10 years	76	38.6
	Accounting /Finance	15	7.6
Respondent function	Human resources	11	5.6
	Information systems	87	44.2
	Marketing and sales	56	28.4
	Research and development	9	4.6
	Others	19	9.6

Preliminary Analyses

Missing data analysis

We conducted an examination of the dataset before starting data analysis, including missing data analysis, non-response bias check, and common method bias check. Using Little's MCAR test, we tested our data set to determine whether it meets the assumption of data missing completely at random (MCAR). The result indicated that the data are missing completely at random (χ^2 (453) = 436.946, p=0.698). Although missing data was both random and minimal, we replaced missing data with a simple mean (Little and Rubin, 1987).

Non-response bias test

Non-response bias was assessed by comparing early and late respondents in terms of annual sales, firm age, and number of employees by t-tests. The results showed there were no statistically significant differences between these groups. We thus determined that non-response bias did not present a problem for this study.

Common method bias check

Because the independent and dependent variables were from the same source and self-reported by the respondents, common method bias might be a threat to this study. We thus examined common method bias using two methods. First, following the guidelines by Podsakoff and his colleagues (2003), we protected respondent-researcher anonymity, provided clear directions, and proximally separated independent and dependent variables to reduce common method bias (Podsakoff et al., 2003). We then tested for bias statistically. Harman's one-factor test (Greene & Organ, 1973) was used to determine whether common method bias is a threat to the validity of this study's results. The unrotated factor solution indicates that no factor accounts for 10 % or more of the variance. To further confirm the conclusion, we ran Lindell and Whitney's (2001) test that used a marker-variable technique in the model by adding an irrelevant marker variable. The maximum shared variance with other variables was 0.013 (1.3%), indicating no common method bias, which suggests that common method bias in our study is not a significant threat to its validity.

Measurement

Wherever possible, all items were adapted from extant literature and modified in the context of big data adoption as needed in this study (see Appendix 2). As the targeted participants were in China, the questionnaire was back-translated into Chinese to adapt to Chinese culture and ensure its accuracy (Brislin, 1970). A panel of researchers and practitioners examined the face validity of the items. The author made the original translation and two PhD students who were both proficient at English and Chinese reviewed it individually. When there was an inconsistency, the three discussed it until an agreement was reached. A panel of

researchers with management information system (MIS) backgrounds and practitioners in the pilot study examined the face validity of the items.

All items used a seven point Likert scale to reflect the degree of participants' agreement (ranging from 1="strongly disagree" to 7="strongly agree"). Each indicator in the study was modeled in a reflective manner. Readiness for change is a multi-level construct in this study, which was adapted from Holt et al. (2007a), including four change recipients' beliefs: appropriateness, management support, change self-efficacy, and personal valence. Unlike items used in other literature to measure readiness for change, the final developed items in Holt et al. (2007a)'s work are based on analysis of depth the meaning of this concept. Personal valence was measured using reverse coded items. Market turbulence was evaluated using Jaworski & Kohli's (1993) and Hult, Ketchen, & Arrfelt's (2007) five-item scale that reveals employees' general perception of customers' demands change in the market. Intention to adopt was adapted from Sarker & Valacich (2010) and Teo, Wei, & Benbasat's (2003) three-item scale that indicates the organizational members' general perception of organizational intention to adopt big data.

Controls

We included three control variables that have been widely discussed to be related to firms' intention to adopt new technology. These are firm size, firm age, and industry type. Firm size is a key factor that can affect big data adoption (Rogers, 2003). It was measured by the number of employees. Firms in different industries may have different needs to leverage and capture the benefits of big data because of industry structure (Manyika et al., 2011). Firms were separated into two categories; manufacturing and service. Firms in almost every industry are trying to adopt big data to win competitive advantage. However, manufacturing industries are more likely to use big data technology to analyze data from machine sensors; service industries

are likely to focus on analyzing customer data. Firm age is another factor that may affect new information technology use performance (Lu & Ramamurthy, 2011). It is represented by the number of years from inception to the present.

Data Analysis and Results

Because of the advantage of examining proposed causal paths among constructs, SEM serves our research purpose better than other analysis techniques such as linear regression (Gefen, Rigdon, & Straub, 2011). The hypotheses presented earlier were tested collectively using the structural equation modeling (SEM) approach and software packages Amos 22 and SPSS 22.

Descriptive Statistics, Reliability and Validity

Table 2 presents the means, standard deviations, Cronbach's alphas, composite CR, AVEs and the construct correlations. The Cronbach's alphas range from 0.844 to 0.896, indicating internal consistency (Bollen & Lennox, 1991). Construct reliability was assessed based on composite construct reliabilities (CR) computed with the formula: $\rho = (\Sigma\lambda_i)^2 / ((\Sigma\lambda_i)^2 + \Sigma\theta_i)$, where λ_i refers to the i_{th} factor loading and θ_i refers to the i_{th} error variance (Hair Jr. et al. 2010, p. 687). As shown in Table 2, CRs ranging from 0.844 and 0.925, greater than the commonly accepted cutoff value of .70 (Gefen, Rigdon, & Straub, 2011), demonstrating good reliability.

The inter-construct correlation matrix is presented in Table 2. To examine discriminant validity, inter-construct correlations below the recommended threshold of |0.7| provide evidence of measure distinctiveness, and thus discriminant validity. No factor correlation is greater than 0.7 in the study, which demonstrates discriminant validity (see Table 2). We further compared the square root of the average variance extracted (AVE) for each construct (on the diagonal) to

the inter-construct correlation. When the square root of the AVE is larger than the corresponding inter-construct correlation estimates, it suggests that the indicators have more in common with the construct they are associated with than they do with other constructs, which provides evidence of discriminant validity (Kline, 2010). As all the square root of the average variance extracted (AVEs) are higher than the corresponding inter-construct correlations, we conclude that the data suggests adequate divergent validity of the measures.

Table 2. Descriptive statistics, correlations, Cronbach's alpha, and square root of the AVEs

Variable	Mean	S.D.	Composite CR	AP	MS	CE	PV	MT	ITA
AP	5.54	0.94	0.853	0.781					
MS	5.12	0.97	0.897	.473**	0.854				
CE	4.78	0.96	0.896	.480**	.603**	0.800			
PV	5.01	1.03	0.863	.181**	.237**	.222**	0.742		
MT	4.74	1.01	0.871	.325**	.373**	.379**	.215**	0.728	
ITA	5.23	0.96	0.844	.407**	.408**	.460**	.284**	.427**	0.843

Note*:* N=197. Square root of the AVEs on diagonal. Each construct of square root of the AVE exceeds the inter-construct correlation for adequate discriminant validity. ** Correlation is significant at the 0.01 level (two-tailed).

AP: Appropriateness; MS: Management support; CE: Change self-efficacy; PV: Personal valence; MT: Market turbulence; ITA: Intention to adopt

An exploratory factor analysis with varimax rotation for all constructs was conducted to test construct validity. Factor loadings for each construct are shown in Table 3. The results indicate that all items loaded on a distinct construct and their factor loadings were greater than 0.5, showing a good convergent validity. The results confirmed the existence of eight observed constructs with eigenvalues greater than 1.0, indicating good discriminant validity.

Table 3. Item Loadings and Cross-loadings

Construct	Items	RFC_A	RFC_MS	RFC_CE	RFC_PV	MT	ITA
Appropriateness (RFC_A)	RFC_A_1	.145	.189	**.813**	.083	.038	.180
	RFC_A_2	.080	.207	**.848**	.043	-.005	.103
	RFC_A_3	.150	.129	**.712**	.110	.076	.083
	RFC_A_4	.065	.147	**.768**	.294	.101	.204
Management support (RFC_MS)	RFC_MS_1	.195	.336	.229	.128	.137	**.738**
	RFC_MS_2	.152	.335	.182	.185	.096	**.809**
	RFC_MS_3	.116	.196	.193	.098	.041	**.868**
Change self-efficacy (RFC_CE)	RFC_CE_1	.155	**.769**	.108	.131	.072	.245
	RFC_CE_2	.097	**.819**	.224	.112	.078	.176
	RFC_CE_3	.177	**.802**	.235	.198	.100	.134
	RFC_CE_4	.126	**.780**	.192	.186	.044	.271
Personal valence (RFC_PV)	RFC_PV_1	.156	.038	.093	.081	**.855**	.063
	RFC_PV_2	.058	.040	.031	.155	**.886**	.104
	RFC_PV_3	.043	.141	.043	.061	**.869**	.031
Market turbulence (MT)	MT_1	**.701**	.266	.124	.246	.056	.016
	MT_2	**.797**	.263	.094	.151	-.022	.113
	MT_3	**.820**	.022	.150	.067	.093	.181
	MT_4	**.864**	.071	.012	.073	.075	.137
	MT_5	**.810**	.027	.134	.135	.126	.018
Intention to adopt (ITA)	ITA_1	.185	.175	.194	**.854**	.125	.127
	ITA_2	.239	.135	.197	**.860**	.105	.142
	ITA_3	.152	.230	.082	**.788**	.120	.097

Note*:* Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

Structural Model Assessment

The goodness-of-fit of the structural model was examined. As shown in Figure 2, the R^2 value of intention to adopt is 0.736. The model chi-square is statistically significant ($\chi2\ (178) = 321.811$, p <.001), which indicates that the exact fit hypothesis is rejected. The value of χ^2/df is 1.808, which indicates a good model fit. However, this test is highly sensitive (Jöreskog and Sörbom, 1988). We therefore examined other measures of goodness-of-fit by using a combination of one of the relative fit indexes and root mean square error of approximation (RMSEA) (Hu and Bentler, 1999). The comparative fit index (CFI) is 0.938, incremental fit index (IFI) is 0.9379 and Tucker Lewis index (TLI) is 0.926, exceeding the cutoff value of 0.90 (Hair et al., 2009). The RMSEA is 0.065 (Byrne, 2001), further indicating that our data adequately fit the measurement model.

Variance inflation factors (VIFs) of the independent variables were also checked for evidence of multicollinearity (Petter, Straub, and Rai, 2007). The results ranged from 1.327 to 2.278. None of the VIF values exceed 5, indicating that multicollinearity is not an issue in our study. We did not conduct post-hoc modifications because of the good fit of the data to the model. With evidence of acceptable fit, we proceeded to test our hypotheses.
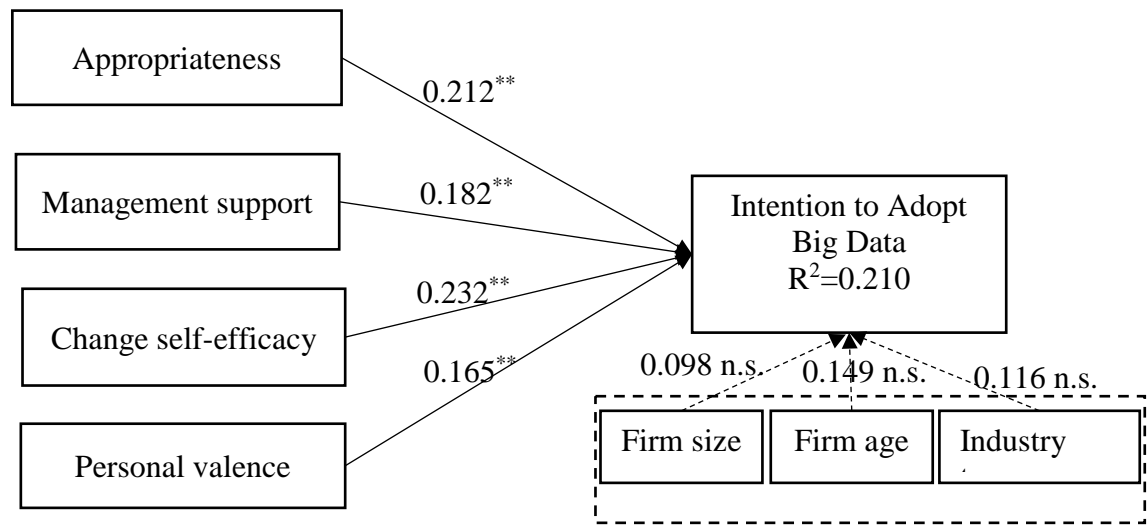
Figure 2. Overview of Direct Effect Model Results

Note: *p<.05, **p<.01, ***p<.001, n.s.=Not significant.

Model fitness: χ^2 (df) = 291.83 (159), p < 0.001, CFI = 0.938, IFI=0.939, TLI=0.925;

RMSEA (90CI) = 0.065 (0.053; 0.077)

The first hypothesis states that appropriateness will positively affect a firm's intention to adopt big data. As shown in Table 4, the path from appropriateness to intention to adopt is significant (β=0.212, p=0.008). Thus, hypothesis 1 is supported. The second hypothesis argues that management support will positively influence firms' intention to adopt big data. The result indicates that the path from management support to intention to adopt is also significant (β=0.182, p=0.006), supporting this hypothesis. Hypothesis 3 states that change self-efficacy within the organization will affect big data adoption. Results show that the path from change self-efficacy to intention to adopt is significant (β=0.232, p=0.005). The path from personal valence to intention to adopt is also significant (β=0.165, p=0.008). Thus, hypotheses 3 and 4 are both supported. The three control variables, firm size, firm age, and industry type are found to be non-significant in the

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analysis affecting organizational intention to adopt big data and are not address in the discussion below.

Table 4. Structural Modeling Results

Relationships	β	t-Value	p-Value	Conclusion
H1. AP → ITA	0.212**	2.361	0.008	H1 supported
H2. MS → ITA	0.182**	2.384	0.006	H2 supported
H3. CE → ITA	0.232**	2.645	0.005	H3 supported
H4. PV → ITA	0.165**	2.395	0.008	H4 supported

Note: $*p<0.05$, $**p<0.01$, $***p<0.001$.

AP: Appropriateness; MS: Management support; CE: Change self-efficacy; PV: Personal valence; MT: Market turbulence; ITA: Intention to adopt

To investigate the moderating role of market turbulence between organizational readiness for change and intention to adopt big data as posited in H5a –H5b, we conducted a multi-group analysis estimated in AMOS. The sample was first split at the median value of market turbulence (median = 4.80, S.D. = 1.01) into two groups, low market turbulence (n = 103) and high (n = 94) market turbulence. The result indicated in a good fit to the data ($\chi2$ (df) = 438.880 (230), p < 0.001, $\chi2_/$ df=1.908), CFI = 0.908, IFI=0.910, TLI=0.905; RMSEA (90CI) = 0.068 (0.059; 0.078)).

Appropriateness in the low (β=0.183, p=0.124) and high market turbulence groups (β=0.248, p=0.010) is significantly different. Thus, H5a was supported. Management support in the low (β=0.110, p=0.276) and high market turbulence groups (β=0.150, p=0.208) was not significantly different. H5b was not supported as hypothesized. Change self-efficacy in the low (β=0.216, p=0.037) and high market turbulence groups (β=0.236, p=0.026) was not significantly different either, indicating a lack of support for H5c. However, the effect of personal valence on for big data

adoption intention was significantly different between the two groups (β=0.098, p=0.165 for the low turbulence group and β=0.379, p=0.011 for the high turbulence group), implying support for H5d.

Table 5. Moderating Effects Result

Relationships	Group	β	t-Value	p-Value	Conclusion
H5a. MT: AP → ITA	low	0.183	1.539	0.124	H5 supported
	high	0.248**	2.586	0.010	
H5b. MT: MS → ITA	low	0.110	1.090	0.276	H6 not supported
	high	0.150	1.259	0.208	
H5c. MT: CE → ITA	low	0.216*	2.088	0.037	H7 not supported
	high	0.236*	2.228	0.026	
H5d. MT: PV → ITA	low	0.098	1.390	0.165	H8 supported
	high	0.379*	2.537	0.011	

Note: *p<0.05, **p<0.01, ***p<0.001.

AP: Appropriateness; MS: Management support; CE: Change self-efficacy; PV: Personal valence;

MT: Market turbulence; ITA: Intention to adopt

Discussion

Implications for Theory

This study extends the understanding of open-systems theory in the context of big data adoption; this indicates that big data adoption is a synthesis of internal factors and external factors. Research from the change management view regarding new technology adoption in an

organization is still limited (Argote & Hora, 2017). It is widely acknowledged that big data offers firms new opportunities to develop competitive advantage. Adopting new technology to build competitive advantage in a turbulent environment has long been a challenge for scholars to study (Pavlou & El Sawy, 2006).

This study provides evidence that extends our understanding of the big data adoption process from a change management view and discusses some new critical factors of big data adoption. The empirical results confirm that there is a direct effect of readiness for change on the adoption of big data. This highlights organizational readiness for change on the adoption of new technology. Higher readiness for change can make the adoption process proceed more smoothly. Failure to create readiness for change may cause potential problems during the implementation process. This study extends the current understanding of the factors that may affect the big data adoption decision-making.

Past studies have discussed the relationships among employees' personalities, organization context, and resistance to change (Oreg, 2006); they have not addressed the issue of how external factors (i.e., market turbulence) and readiness for change together affect organizational adoption of big data. This study fills a significant gap in understanding the effect of organization members' beliefs toward new technology adoption and external market uncertainty on big data adoption decision making. Market turbulence, as a moderator, has been partially supported, indicating that adoption strategy may change under different market conditions. In this study, higher market turbulence is more likely to drive firms to adopt big data.

Implications for Practice

It is commonly believed that the use of new technology enables changes in organizations. However, to be fully successful, employees must believe in the implementation and its perceived

benefits. Big data as a new technology innovation offers firms new opportunities to gain a competitive advantage. However, it is still difficult for practitioners to understand to the process of big data diffusion in a turbulent environment. At an early stage of big data adoption, any factor may affect decision makers' decision (Sun et al., 2016). This study helps managers understand the critical role of organizational members' beliefs and attitudes toward the change and unveils the importance of creating readiness for change for the adoption of big data.

All four factors of readiness for change have been examined with survey data. The results indicate that all these factors have a direct effect on the adoption of big data. This implies that executives should develop good change readiness before embracing a new technology adoption. This can increase the odds of a successful adoption of big data. For example, organizations can create a sense of urgency by reflecting external competitive pressures. This may help employees support adoption of big data. Management support is another significant factor that influences big data adoption. Accordingly, managers are advised to have an active attitude toward and provide enough support to encourage employees and help facilitate the adoption strategy. Because of the important role of personal valence, firms should also clarify the intrinsic and extrinsic benefits for employees and assure them that the adoption decision will be beneficial both to the organization and to the employees individually.

External conditions are expected to affect the organizational decision to adopt a new technology innovation. Our results indicate that market turbulence influences appropriateness and personal valence under high market turbulence but not under low market turbulence. Our findings suggest that the effects of management support and employee change self-efficacy are stable regardless of market turbulence. This suggests that firms should put energy and resources toward supporting the appropriateness of the change and highlighting personal benefits of the change for

employees as market turbulence increases. However, firms should also seek to maintain a continuous state of high management support regardless of market conditions. Continuing to support and prepare employees for all changes will facilitate future decisions to adopt technology.

Limitations and Directions for Future Research

There are three limitations of this study. Data collected from the Chinese culture may decrease the generalizability to other nations. However, this study provides great insight on Chinese new technology adoption in practice and sheds light on big data adoption for developing countries. However, in order to make our study more generalizable, future researchers should collect data from other countries or cultural settings as well. Second, as a developing country, market turbulence in China is relatively higher than in other developed countries. The level of market turbulence may affect the findings. Third, from an organizational readiness for change perspective, we can predict organizational intention to adopt big data. However, the R square is not as high as expected. It indicates there are more and possibly confounding factors that may affect organizational intention to adopt big data.

In response to the above limitations, we call for future research to extend our work. For example, data could be collected from other countries or from different market settings to make the study more generalizable and to determine the impact these differences have on adoption. A cross-culture study may elicit interesting differences. To fully predict organizational intention to adopt big data, future studies should explore other factors and test their relationships with adoption intention. Other theories or perspectives to explain organizational intention to adopt big data are also encouraged.

Conclusion

A theoretical framework, grounded in open-systems theory, was developed. Empirical analyses were conducted and verified the relationships among organizational readiness for change, market turbulence, and intention to adopt big data. Appropriateness, management support, change self-efficacy, and personal valence positively influence the big data adoption intention. Market turbulence partially moderates the relationship between organizational readiness for change and the intention to adopt big data. The findings provide several theoretical and managerial implications.

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Readiness for Change (Holt, Armenakis, Feild, & Harris, 2007a) (1 = strongly disagree; 7 = strongly agree)

Appropriateness

1. I think that the organization will benefit from this change.

2. This change will improve our organization's overall efficiency.

3. This change matches the priorities of our organization.

4. In the long run, we feel it will be worthwhile for us if the organization adopts this change.

Management Support

1. Our senior leaders have encouraged all of us to embrace this change.

2. Our organization's top decision makers have put all their support behind this change effort.

3. Our organization's most senior leader is committed to this change.

Change Self-efficacy

1. When we implement this change, we feel we can handle it with ease.

2. We have the skills that are needed to make this change work.

3. When we set my mind to it, we can learn everything that will be required when this change is adopted.

4. Our past experiences make us confident that we will be able to perform successfully after this change is made.

Personal Valence

1. I am worried I will lose some of my status in the organization when this change is implemented (R).

2. This change will disrupt many of the personal relationships I have developed (R).

3. My future in this job will be limited because of this change (R).

Market Turbulence (Jaworski & Kohli, 1993; Hult, Ketchen, & Arrfelt 2007) (1 = strongly disagree; 7 = strongly agree)

1. In our kind of business, customers' product preferences change quite a bit over time.

2. Our customers tend to look for new products all the time.

3. We have demand for our products from customers who never bought them before.

4. New customers have product needs that are different from our existing customers.

5. We continuously cater to many new customers.

Intention to Adopt (Sarker and Valacich, 2010; Teo, Wei, and Benbasat, 2003) (1 = strongly disagree; 7 = strongly agree)

1. Assuming that we had the ability to adopt some form of big data technology for my company, we intend to do so.

2. Given that my company had access to some form of big data technology, we predict that my company would use it.

3. My company plans to adopt some form of big data in the next 18 months.

Note: R = item was reverse scored.

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INFORMED CONSENT
for a Research Study entitled
"Factors Affecting Organizational Adoption of Big Data in China"

Principle Investigator: Shiwei Sun – PhD student at Department of Aviation& Supply Chain Management, Harbert College of Business, Auburn University

Purpose of the Study: The purpose of this research study is to explore the critical factors that can affect the adoption of big data in China.

Procedure: If you agree to participate, complete questionnaires about your opinion on big data adoption based on your working experience, and general demographic information on paper questionnaire. The approximate total time to complete the questionnaires should be about 15-20 minutes.

Confidentiality: At all times, your privacy will be respected. At no time will individual identifying information be provided to outside sources unless required by law.

Expected Risks: There are no foreseeable risks to you by completing this survey, as all results will be kept completely confidential.

Expected Benefits: No direct benefit for your response.

Voluntary Participation: Participation in this study is voluntary. You may choose not to participate without negative consequences. If you do decide to participate, you can change your mind at any time and withdraw from the study without negative consequences. Your decision whether or not to participate will not jeopardize your future relations with Auburn University, the Department of Aviation and Supply Chain Management, or your grade in class.

Use of Research Results: Results may be presented at research conferences and in scientific publications by the principal investigator. Results will be presented in aggregate form only. No names or individually identifying information will be revealed.

Future Questions: If you have any questions concerning your participation in this study now or in the future, you can contact the **principal investigator, Shiwei Sun**, at 334-444-4000 or via e-mail szs0100@auburn.edu

Consent to Participate: I have read or had read to me all of the above information about this research study, including the research procedures, possible risks, side effects, and the likelihood of any benefit to me. The content and meaning of this information has been explained and I understand. All my questions, at this time, have been answered. I hereby consent and do voluntarily offer to follow the study requirements and take part in the study.

If you have questions about your rights as a research participant, you may contact the Auburn University Office of Research Compliance or the Institutional Review Board by phone (334)-844-5966 or e-mail at IRBadmin@auburn.edu or IRBChair@auburn.edu.

HAVING READ THE INFORMATION PROVIDED, YOU MUST DECIDE WHETHER OR NOT YOU WISH TO PARTICIPATE IN THIS RESEARCH STUDY. YOUR SIGNATURE INDICATES YOUR WILLINGNESS TO PARTICIPATE.

_____   _____

Participant's signature   Date   Investigator   Shiwei Sun,   Date

_____

Printed Name

ESSAY 3: BIG DATA CAPABILITIES, ORGANIZATIONAL DECISION-MAKING, AND BUSINESS VALUE CREATION

Introduction

When a business environment is becoming more volatile, firms face increasing challenges when making an effective strategic decision and coping with the market turbulence (Pavlou & El Sawy, 2006). Internal operations and the external environment of the firm exacerbate uncertainty, making prediction difficult. To achieve effective decision-making, timely processing of large volumes and varieties of information that can be enhanced by a number of IT-enabled supporting, monitoring, or learning systems is required. It is acknowledged that IS applications can be designed and used to enhance managerial capacity (Tanriverdi et al., 2010).

Data is increasingly considered the next big thing from which firms can create or enhance value (Rotella, 2012). Data are worthless for decision making until they are processed into useful information (Gandomi & Haider, 2015). Business decision making is based on large volumes of information. A quantitative mindset can yield powerful benefits (Davenport & Harris, 2007). In addition to locating reliable information sources, the process of acquiring and analyzing that information is a focus for many firms. Big data innovation is a potential solution. Firms can derive value from data analytics and use the results to drive growth. Recognizing the value of big data capability, many firms are investing in big data technologies. The adoption and use of big data capabilities to create business value has become a strategic consideration for many organizations (Lee et al., 2014).

Big data has evolved into a set of technologies (Xu, Frankwick, & Ramirez, 2016) that facilitate developing insights. Firms adopt big data to create valuable intelligence by analyzing

massive volumes of data in real time. From an analytic method view, big data analytics are presented in three categories, including descriptive techniques, prescriptive techniques, and predictive techniques (Hazen et al., 2016). Correspondingly, big data capabilities can be divided into three parts, including analytical capability, predictive capability, and decision support capability (Sun et al., 2015). One of the purposes of developing these capabilities is to refine data and enhance decision-making. As the quality of decision-making improves, enhanced business value will result.

The decision making process refers to "the conversion of information into action" (McClure, 1978, p. 382). In the era of big data, data-driven decision-making (DDDM) has been proven to have an important impact on firm performance. Brynjolfsson, Hitt, and Kim (2011) indicate that the more data-driven a firm is, the more productive the firm will become. They found that firms adopting DDDM will have a 56% higher performance in productivity and output than their expectations from other investments. LaValle et al. (2011) find that top performers in industries are relying more on business analytics results to support decision making. McAfee and Brynjolfsson's (2012) analysis also shows that the more companies characterized themselves as data-driven, the better they performed on objective measures of financial and operational results. Scholars have widely acknowledged that big data is a business solution that can generate business value and improve data-driven decision-making (McGlinchey, 2013; LaValle et al., 2011). Researchers have begun to discuss how big data can improve the quality of decisions (Mikalef et al., 2017; Sharma, Mithas, and Kankanhalli, 2014). Compared with traditional decision-making, data-driven decision making minimizes human intervention. Using data to facilitate high-quality decisions and the business value that results is of increasing interest to both scholars and practitioners. However, to the best of our knowledge, the effects of using big

data to improve the decision making process have not been empirically tested. We investigate the decision making effects produced by the use of big data.

Effective use of big data leads to business success. Its role has been well recognized for firms in operations research (e.g., Hazen et al., 2016), marketing (e.g., Arthur, 2013; He, Wang, & Akula, 2017), supply chain management (e.g., Chen, Preston, & Swink, 2015), and many other aspects. The capabilities of big data have become a focus in information systems (IS) research and industry. However, most studies focus on the technical aspects of big data (e.g., Mikalef et al., 2017) or are conceptual work discussing how big data use can improve decision quality and then generate business value (e.g., Sharma, Mithas, and Kankanhalli, 2014). There is a lack of empirical research to evaluate business value creation by big data (Mikalef et al., 2017; Wamba, et al., 2015). Scholars, therefore, call for research on big data use and its impact on organizational performance (e.g., Sharma, Mithas, and Kankanhalli, 2014).

How big data creates business value in supply chains (Hazen et al., 2016; Cerchione & Esposito, 2016), customer relations, production and operations (Hazen et al., 2016) is not widely investigated. Likewise, the process of how big data technology creates business value through improving decision quality has not yet been well explored. The fundamental purpose of this study is to empirically explore relationships among big data capabilities, organizational decision making, and business value creation.

The remainder of this article is structured as follows. We first present a literature review discussing the salient points of dynamic capabilities and the process level-based view. Big data capabilities, organizational decision making, and business value creation are also discussed in this section. Next, we develop the hypotheses that present the proposed relationships among constructs. Following this, we describe the research methodology and our data analysis before

presenting the results. We close with a discussion as to how our research contributes to both theory and practice.

Literature Review

Theoretical Foundation

Dynamic capabilities are "firm's ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments" (Teece, Pisano, & Shue, 1997, p. 516). Scholars maintain that big data use is an organizational dynamic capability useful to derive competitive advantage (Chen, Preston, & Swink, 2015). By generating business insights across various activities, big data help firms anticipate and react to market change. This ability is a key characteristic of dynamic capabilities (Eisenhardt & Martin, 2000). Compared with other capabilities, dynamic capabilities are regarded as strategic options (Kogut & Zander, 1996), which can offer firms new insights into business opportunities. A data-centric capability can support organizational decision processes. Big data as part of firms' information assets enhances decision making and insights.

We argue that big data capabilities can have a direct effect on organizational decision-making, and in turn on business value creation. Big data analytics include three broad types. These are descriptive, predictive, and prescriptive analytics (Saumyadipta, Rao, & Rao, 2016). Descriptive analytics summarize historical data and may be the first step toward a more advanced process. Predictive analytics are used to forecast upcoming events. Prescriptive analytics are relatively new and primarily involve recommending potential actions; they are specifically tasked with decision making improvement. Thus, big data use in creating business

value in this study can be measured from three key dimensions, analytical capability, predictive capability, and decision support capability.

Successful use of information technology is evident when IT is embedded in organizational processes from manufacturing to marketing. Alignment between IT use and business activities has been well studied. Organizational structures are interconnected in a value chain, in which IT and business activities are aligned. The objective of the use of IT is to improve the process and enhance each business activity. A process-level view can be fully used to exhibit this alignment. From a process-level view, the business value of firm performance can be measured from different aspects, including supplier relations, production and operations, service enhancement, sales and marketing, and customer relations (Tallon, 2011). Big data positively affects these aspects. However, importance varies throughout the whole supply chain. For example, big data is important in operations management but more important in customer relations (Schroeck et al., 2012). We focus on the aspects that are most likely to produce business value. We examine the relationship between big data and supplier relations, production and operations, and customer relations (LaValle et al., 2011).

Big Data Capability

The role of data analytics is defined as: "the extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions." (Davenport & Harris, 2007 p. 7). Big data analytics are comprised of three main techniques: including descriptive, predictive, and prescriptive analytics (Saumyadipta, Rao, & Rao, 2016). This taxonomy has the advantage of reflecting business problems and big data techniques. Big data, as an advanced data analytics tool, can help organizations achieve many goals through its unique capabilities.

Benefits from big data may be found in production, R&D, marketing, among others. Big data also serves as the foundation for organizational innovation, competition, and productivity (Lycett, 2013). Big data is now a hot topic across industries but it is different from previous business analytics innovations that served primarily as technical functions. Not only does it facilitate an amount of data that couldn't be processed by a traditional approach, but it can also provide business solutions with its unique prediction and decision support capabilities.

IT capability is described as a formative second-order construct with different dimensions (Chen et al., 2014). To date, its components are still being explored (Mikalef et al., 2017). Scholars try to identify big data capability based on theories. For example, Gupta & George (2016) identified tangible and intangible resources, including basic resources, technology, technical skills, managerial skills, a data-driven culture, and intensity of organizational learning, which together form big data capability.

This study focuses on the effect of big data functions on business value creation. Big data capability has been confirmed as a higher construct (Gupta & George, 2016). In this study it is also viewed as a latent construct (see Figure 2), conceptualized as a second-order factor formed by three first-order facets (analytical capability, predictive capability, and decision support capability) (see Figure 1). Sun et al. (2015) provide the foundation for this study as we adopt their work on these capabilities.
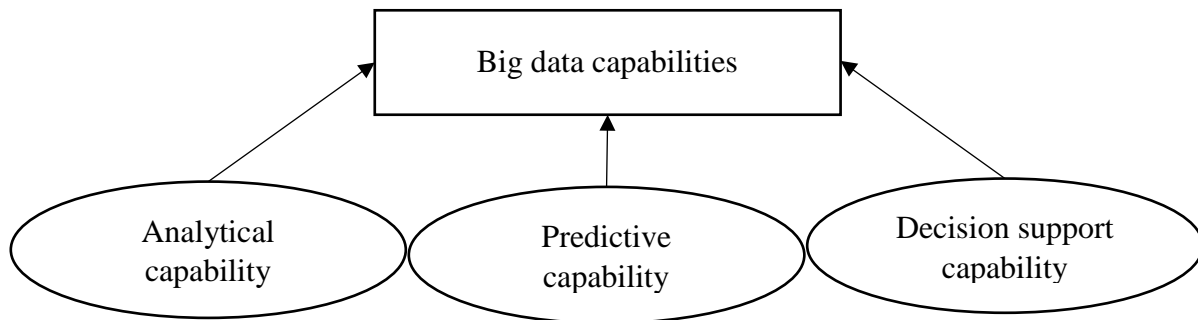
Figure 1. The Proposed Higher-Order Model for Big Data Capabilities in Creating Business Value (adopted from Sun et al., 2015)

Analytical capability

Big data is characterized by its advanced business intelligence and analytics (BI&A) functions to work with large and disparate amounts of data. It was originally used to describe large data sets (Chen, Chiang, & Storey, 2012), the term now focuses more on analytics and technologies that support both. Hadoop, MapReduce and NoSQL are examples of big data platforms that can be used to process large-scale data. Descriptive techniques are a fundamental technique of big data analytics and the simplest form; they can help firms describe what has happened and uncover what is happening (Nguyen et al., 2017; Souza, 2014). Generally, the process identifies patterns in data, allowing a descriptive interpretation of the results. The quicker this data can be analyzed, the faster the firm can act. Analytical capability may be described as an organization's overall ability to capture, store, and process/analyze large volumes of data at or near real-time. This speed sets it apart from more traditional approaches. It provides reports that offer historical insights regarding the company's production, sales, and other information, but the history may be much more recent than a traditional approach would have allowed. Descriptive analytics are a primary characteristic of analytical capability.

Predictive capability

Predictive analytics is the second technique of big data analytics and helps firms predict future events (Souza, 2014). Predictive capability is an organization's overall ability to use analysis results for prediction at any organizational level. Firms in dynamic environments have high motivation to measure trends more precisely (McAfee, A., & Brynjolfsson, 2012; Wamba et al., 2015) to benefit from insights gained. In addition, the ability to make rapid predictions on which to act is paramount to crating business value. Technologies that support this are necessary. Forrester assessed current big data technologies and found that predictive analytics is the only technology that can bring high business value for a lasting time (Press, 2016). Use of predictive analytics leads to predictive capability.

Decision support capability

Prescriptive analytics is the third technique and most often follows the other two. It includes decision-making mechanisms and tools (Souza, 2014) and is used to improve decision making. Decision support capability is an organization's overall ability to use information (e.g., big data analysis results) to support managerial decision-making at each organizational level. From the strategy-as-practice view, Whittington (2014) argued that big data technologies have an effect on developing a strategic blueprint. Big data influences the distinctive practices that evolve organizational strategy. In order to create real value for organizations, big data must be combined with decision support capabilities (Power, 2014). With the support of prescriptive analytics, firms can improve decision making that can optimize and improve business activities throughout the organization, from production and operations to long-term strategy making.

Organizational Decision Making

Data-driven decision making (DDDM) refers to the practice of basing decisions on the results of data analysis rather than purely on subjective intuition (Provost & Fawcett, 2013). Currently, there is a growing tendency to amass data. The challenge for firms is how to exploit this asset more effectively. Decision makers now place more emphasis on data support to improve decision making.

Decision making speed

Decision making speed refers to "the time when a decision maker recognizes the need to make some decision, to the point in time when he/she renders judgment" (Leidner and Elam, 1993, p. 207). In the current business environment, rapid decision making has become critical for the survival of and more importantly for the growth of a firm. With the support of big data, some decision-making can be automated (Provost & Fawcett, 2013).

Data sets from different sources may be challenging for firms to use in decision making. As a dimension, decision making speed is becoming more important in various contexts, especially in customer management, because real-time responses to the market are more necessary than in the past. A late response to customer service requests is likely to result in customer attrition (Bharadwaj et al., 2013). Firms increasingly invest in new technology to improve their decision making outcomes. Big data has more capability to capture and process data in real-time (Bharadwaj et al., 2013), thus facilitating speed.

Extent of analysis

Even though fast decision making is essential to firms' growth, extensive analysis also plays a key role for top managers. Big data can be used to target more effective interventions

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throughout the organization (Wamba et al., 2015). Available data include web logs, social media, call records, video archives, and large-scale e-commerce. There are seven widely used techniques during business value creation. They are association rule learning, classification tree analysis, genetic algorithms, machine learning, regression analysis, sentiment analysis, and social network analysis (Stephenson, 2013), all of which are supported by basic and advanced big data technologies. Hence, big data allows decision-making at a massive scale (Provost & Fawcett, 2013) with disparate and dispersed data to support breadth of analysis.

Business Value Creation

IT business value describes how and to what extent the application of IT contributes to organizational performance (Melville, Kraemer, & Gurbaxani, 2004). There are many ways to measure organizational performance using new information technology. Traditionally, financial indicators such as return on investment (ROI) and return on assessment (ROA) are used to assess performance (Gupta & George, 2016). In contrast to the traditional indicators, we are more interested in how business value is created across different business areas, from supplier relations to customer relations. As suggested by previous research, the value impacts of big data can be assessed at the business process level because this view can explain the organizational level of business value creation (Tallon, 2007). From this view, value created by big data can be evaluated from various aspects. Firms using business analytics achieve five times better performance than those who don't use any business analytics (LaValle et al., 2011).

Studies have shown that results obtained after big data analyses can be measured from different aspects. For example, Wamba et al. (2017) used firm performance to measure use results. Firm performance as a latent construct includes two reflective second-order components, financial performance and market performance (Wamba et al., 2017). Big data business value

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creation in this study is also proposed as a latent construct (see Figure 2), conceptualized as a reflective second-order factor. It can be specifically measured from three business activities in this study, including supplier relations, production and operations, and customer relations.
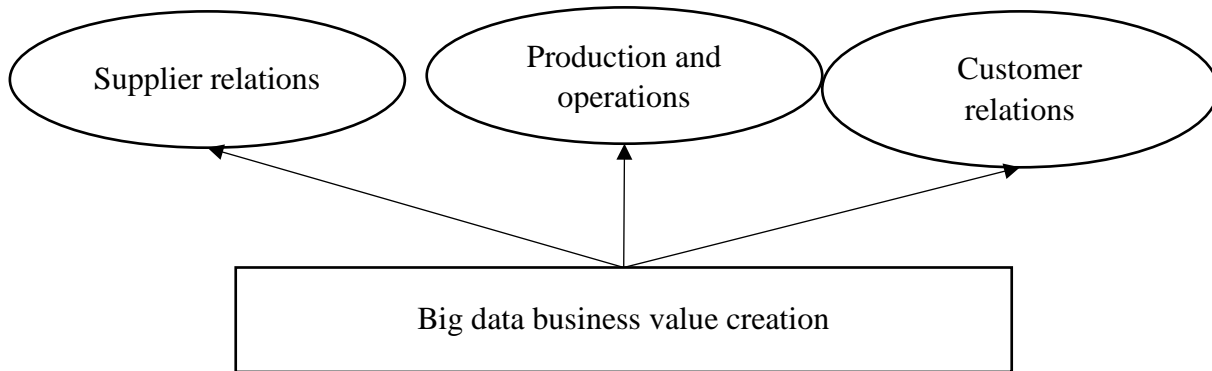
Figure 2. The Proposed Higher-Order Model for Big Data Business Value Creation

Supplier relations

Big data use in supply chain management has become common in the past few years (Nguyen et al., 2017). Supplier relations outcomes may include closer links with suppliers, a monitoring process with suppliers on product and service quality improvement, a monitoring process on delivery times, among others. Big data analytics solutions help improve supplier selection and build optimized knowledge management systems in supply chains to improve firm performance (Hazen et al., 2014; Schoenherr & Speier, 2015; Waller & Fawcett, 2013).

Production and operations

Value created from production and operations include production throughput improvement, labor productivity increase, flexibility, equipment utilization enhancement, and streamlined operations advancement. According to the report from McKinsey Global Institute, big data is beneficial to the entire manufacturing value chain (Manyika et al., 2011). Its implementation is likely to improve product manufacturing and equipment management during

production and operations activities (Li et al., 2015). Specifically, with the support of big data, product testing and quality control can be better monitored, equipment wear can be more precisely estimated, and equipment energy efficiency can be increased.

Customer relations

Value created from customer relations include responses to customer needs, after-sales service and support enhancement, distribution speed, and customer loyalty creation. Building customer relations is not only to persuade customers to purchase again, but also to keep existing customers loyal to the firm. Analysis and action based on that analysis can create long-term customer stickiness, loyalty, and enhanced relationships. In fact, customers today have more knowledge toward products and services selection than ever before, making it difficult to anticipate customers' needs and make effective decisions to satisfy them. Big data provides a good solution to solve this issue, especially given the amount of available social media. Facebook and other social media offer platforms to help understand customer preferences and perception regarding existing products. The role of big data in better serving customers has been highlighted by many scholars. For example, Schroeck et al. (2012) emphasized that big data is used to target customer-centric outcomes and make the organization more customer oriented.

Organizational Innovativeness

Organizational innovativeness is a firm's culture to indicate its openness and propensity to accept new innovations. It is "the capacity to introduce of some new process, product, or idea in the organization" (Hult, Hurley, & Knight, 2004, p.431). Many firms believe innovating to achieve competitive differentiation is a top business challenge (Hurley and Hunt, 1998). Because of the substantial uncertainty when implementing a new innovation, innovativeness is particularly important for firms (LaValle et al., 2011). We suggest organizational innovativeness

can affect the outcomes of implementing a new innovation; those outcomes may include both enhanced organizational decision making and business value creation.

Hypotheses Development

The Impact of Big Data Capabilities on Organizational Decision-Making

The application of big data can enhance organizational decision making (Mikalef et al., 2017). Big data is not only involved when large amounts of data exist, but also to facilitate the speed and varieties of data. Stronger competition and expanding globalization requires that firms make timely decisions, a process that is a purpose of analytics (Chen, Chiang, & Storey, 2012). This may require more advanced tools to use, such as those offered by big data technologies. In turn, the process will support faster decisions. Big data capabilities can support automated decision making at a massive scale (Provost & Fawcett, 2013) in nearly every industry, including e-commerce, manufacture, healthcare, finance and public service (Chen, Chiang, & Storey, 2012).. Thus, we hypothesize that

Hypothesis 1a: Big data capabilities will positively influence organizational decision-making speed

Hypothesis 1b: Big data capabilities will positively influence the extent of organizational decision-making analysis

The Impact of Organizational Decision-Making on Business Value Creation

Speedy decision making speed is associated with organizational performance and competitive advantage (Leidner and Elam, 1993). Much evidence has indicated that business performance can be improved substantially via big data applications (Tambe, 2012).

Effective use of big data techniques helps organizations acquire more suppliers' credit, reduce cost of production, better manage inventory, and gain leverage over its competitors. An integration of real time supplier performance information in a system enhances understanding of supplier relationships and key activities, services and deliverables in a supply chain (Tan et al., 2015). Order-to-delivery times can be shortened, visibility into supplier quality levels may be enhanced, and prediction accuracy may be increased. This could help firms evaluate suppliers' capabilities. Over time, a maximized value relationship can be developed with suppliers. Similarly, big data will also affect production and operations management, as well as customer relations. Thus, we hypothesize that

Hypothesis 2a: Decision-making speed will positively influence the business value created from supplier relations

Hypothesis 2b: Decision-making speed will positively influence the business value created from production & operations

Hypothesis 2c: Decision-making speed will positively influence the business value created from customer relations

With the help of big data technology, data of great depth can utilized. Data appear in various forms. The most common forms are video, text, and voice (Siau, Ee-Peng, & Shen, 2001). For example, customer purchasing data might be the most commonly analyzed structured data. Customer information generated from social networks is the most popular unstructured data used for analysis. Data may be retrieved from e-mail and log files. Even transient data such as digitally-borne TV broadcasts and telephone conversations may be captured and analyzed.

With the support of big data technology, marketers can mine copious data generated from transactions to create useful customer information to make better decisions. For example,

sentiment analysis of messages in social networks and text messages can be conducted to understand customers' preferences. Valuable business insights can also be uncovered by the predictive capability of big data. For example, by analyzing social media data, firms can predict customers' buying behaviors. By unearthing valuable information from these data, firms can have a better understanding of customer needs and better serve those customers. After-sales service and support can also be improved, which could also lead to a better relationship between firms and customers. Thus, we hypothesize that

Hypothesis 3a: Decision-making analysis extent will positively influence the business value created from supplier relations

Hypothesis 3b: Decision-making analysis extent will positively influence the business value created from production & operations

Hypothesis 3c: Decision-making analysis extent will positively influence the business value created from customer relations

The Moderating Effect of Organizational Innovativeness

Organizational innovativeness can affect the outcome of implementing a new innovation. A more innovative firm will have more motivation to utilize new innovations and respond to market demands (Hurley and Hunt, 1998). Organizational inertia is more likely to happen in a less innovative firm. A firm with a culture of innovativeness may have a better understanding of big data use to improve decision quality and firm performance. Decision makers in an innovative firm are more likely adopt new innovations to improve decision making quality. Thus, we hypothesize that

Hypothesis 4: Organizational innovativeness will moderate the effect between big data capabilities and organizational decision-making

Hypothesis 4a: Organizational innovativeness will moderate the effect between big data capabilities and organizational decision-making speed

Hypothesis 4b: Organizational innovativeness will moderate the effect between big data capabilities and decision-making analysis extent

Hypothesis 5: Organizational innovativeness will moderate the effect between organizational decision-making and business value creation

IT capabilities often produce business value by improving intermediate business processes (Melville, Kraemer, & Gurbaxani, 2004). Organizational decision making plays a role in optimizing the business processes. Internal or external factors may play a mediating or moderating role in the achievement of organizational performance. To show the proposed relationships among big data capabilities, organizational decision making, and IT business value, we present our conceptual model in Figure 3. Organizational innovativeness may play a moderating role in the relationships.
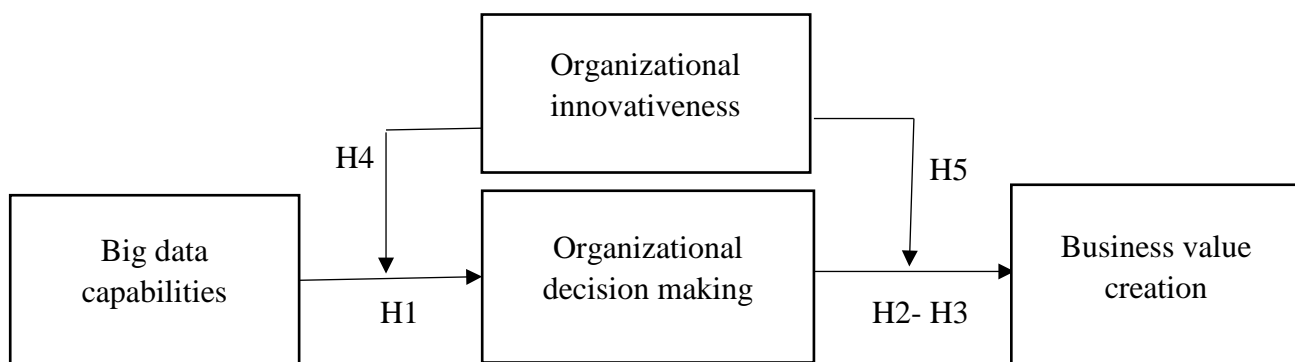

Figure 3. Conceptual Framework

Methodology

Sampling Frame

A survey-based methodology was selected. Before distributing the questionnaires, a pilot test was completed to check the quality of the survey by using a sample of 15 IT background managers in an MBA program in China. The results and their feedback helped us identify poor performing items, improve the back-translation accuracy and reword a few items that were not clear. As the respondents are experts in this area, their assessment also increased the content validity.

As the targeted participants were in China, the questionnaire was first developed in English and then back-translated into Chinese to adapt to Chinese culture and ensure its accuracy (Brislin, 1970). A panel of researchers and practitioners examined the face validity of the items. After researchers translated the instrument, two Ph.D. students who were both proficient in English and Chinese reviewed it individually. When there was an inconsistency, the researchers and students together discussed it until an agreement was reached. A panel of researchers with management information system (MIS) background and practitioners in the pilot study examined the face validity of the items.

We collected data from top MBA and EMBA programs in the east of China. Although students at the time of the study while taking on-campus classes on weekends, all respondents had work experience and were employed full time. There is increasing recognition that China is an adopter of new technologies. Firms in China also actively use big data related applications to enhance competitive advantage (Wamba et al., 2017). Thus, data from China can be used to test our hypotheses. Qualified firms in the study are adopters of big data related applications. The individuals were responsible for or significantly involved in decision-making in business activities and had knowledge of the big data practice in their firms. Target respondents were

required to be at least a middle or upper-level IS or business manager in his or her company. We eliminated participants with job titles that did not qualify.

In total, 250 questionnaires were distributed to potential participants and 198 were returned, resulting in a 79.2% response rate. Fourteen responses that were unusable (e.g., too many same-answer responses, too many missing data responses etc.) were removed, leaving 185 for data analysis. Of the respondents, 22.2% were top managers and 77.8% middle managers. Table 1 shows the profile of the respondents.

Table 1. Sample Characteristics (n=185)

Characteristics	Category	Frequency	Percent
Firm size	1-500	18	9.7
	500-1000	32	17.3
(number of employees)	1000-2000	66	35.7
	Over 2000	69	37.3
Total annual revenue	0-100	12	6.5
	100-1000	32	17.3
(USD, millions)	1000-10000	62	33.5
	Over 10000	79	42.7
Firm age	Less than 10 years	25	13.5
	11-20 years	38	20.5
	21-40 years	49	26.4
	Over 40 years	73	39.4
Industry Group	Manufacturing	70	37.8
	Service-oriented	115	62.2
Respondent job title	Top manager (CEO, CTO etc.)	41	22.2
	Middle manager	144	77.8
Respondent working	Less than 3 years	12	6.5
experience (years)	3-10 years	76	41.1
	Over 10 years	97	52.4
Respondent working	Supplier chain management	25	13.5
	Information systems management	37	20
function	Marketing and sales	53	28.6
	Production management	31	16.8

Human resources management	14	7.6
R&D	12	6.5
Others	13	7.0

Preliminary Analyses

We examined the dataset before starting the data analysis, including missing data analysis, non-response bias check, and common method bias check. Using Little's MCAR test, we tested our data set to determine whether it meets the assumption of data missing completely at random (MCAR). The result indicated that the data are missing completely at random (χ^2 (1321) = 1353.924, p=0.258). Although missing data was both random and minimal, we replaced the missing data with a simple mean (Little and Rubin, 1987).

Non-response bias was assessed by comparing early and late respondents in terms of annual sales, firm age, and number of employees by t-tests. The results showed there were no statistically significant differences between these groups. We thus determined that non-response bias did not present a problem for this study.

Because the independent and dependent variables were from the same source and self-reported by the respondents, common method bias maybe a threat to this study. We thus examined common method bias using two methods. First, following the guidelines by Podsakoff and his colleagues (2003), we protected respondent-researcher anonymity, provided clear directions, and proximally separated independent and dependent variables to reduce common method bias during the design of study and data collection processes (Podsakoff et al., 2003). No constructs with correlations were over 0.7. We then tested for bias statistically. Harman's one-factor test (Greene & Organ, 1973) was used to determine whether common method bias is a threat to the validity of this study's results. The unrotated principal components factor solution

indicates that no factor accounts for 10% or more of the variance. To further confirm the finding, we ran Lindell and Whitney's (2001) test that used a marker-variable technique in the model by adding an irrelevant marker variable. The maximum shared variance with other variables was 0.019 (1.9%), indicating no common method bias, which suggests that any common method bias in our study is not a significant threat to its validity.

Measurement

All items were measured on a five-point Likert scale, ranging from strongly disagree (1) to strongly agree (5). Prior to developing the questionnaire, we developed items for big data capabilities. For the newly developed measures, standard scale development procedures were executed (Churchill 1979). First, each construct was defined by specifying the content domain. Following that, a large pool of items was developed, ensuring that these items were in the construct's domain (Sun et al., 2015). From this pool, items were selected based on the frequency discussed in past literature (Churchill 1979). Eight academics categorized the items, discussing each to reach consensus. Third, the selected items were pretested using the sample of 15 IS scholars. The result was refined based on the pretest result.

All non-developed items were adapted from existing research. Organizational innovativeness was evaluated with five items adapted from Venkatesh and Bala, 2012. Organizational decision making includes decision making speed and the extent of analysis. These items were adapted from Leidner, Carlsson, Elam, & Corrales, 1999 and Leidner & Elam, 1993, with three and four items respectively. Big data business value creation was assessed with three subscales adapted from Tallon, 2011, including supplier relations, production and operations, and customer relations. Minor modifications were made based on the big data use context. All final measurement items can be found in Appendix 4.

Data Analysis and Results

Partial least squares (PLS) regression was chosen to analyze the data because it has many advantages over other analysis techniques, such as moderating effect testing and second-order formative factor processing. As a component-based structural equation modeling (SEM) approach, it can examine proposed causal paths among constructs (Gefen, Rigdon, & Straub, 2011).

Descriptive Statistics, Reliability and Validity

Means, standard deviations, Cronbach's alphas, composite CR, AVEs and construct correlations are presented in Table 2. The reliability of the two second-order constructs (big data capabilities and business value creation), formed by weighted sums of their first-order constructs, is also presented. As shown in Table 2 and Figure 4, the correlations among the first-order factors for big data capabilities were 0.798, 0.854, and 0.859 (p < 0.01); the correlations among the first-order factors for business value creation were 0.798,0.866, and 0.784 (p < 0.01).

The Cronbach's alphas range from 0.895 to 0.953, indicating internal consistency (Bollen & Lennox, 1991). Construct reliability was assessed based on composite construct reliabilities (CR) computed with the formula: $\rho = (\Sigma\lambda_i)^2 / ((\Sigma\lambda_i)^2 + \Sigma\theta_i)$, where λ_i refers to the i_{th} factor loading and θ_i refers to the i_{th} error variance (Hair et al. 2010, p. 687). As shown in Table 3, CRs ranging from 0.91 and 0.97, greater than the commonly accepted cutoff value of .70 (Gefen, Straub, & Boudreau, 2000), demonstrate reliability.

The inter-construct correlation matrix is also presented in Table 2. To examine discriminant validity, we compared the square root of the average variance extracted (AVE) for each construct (on the diagonal) to the inter-construct correlation. When the square root of the AVE is larger than

the corresponding inter-construct correlation estimates, it suggests that the indicators have more in common with the construct they are associated with than they do with other constructs, which provides evidence of discriminant validity (Kline, 2010). Our results show no deviations from these guidelines for any first order construct; we conclude that the data suggests adequate divergent validity of the measures.

Table 2. Descriptive statistics, correlations, Cronbach's alpha, and square root of the AVEs

Variable	Mean	S.D.	Cronbach's alpha	Composite CR	BDC	AC	PC	DSC	OI	DMS	EOA	BVC	SR	PO	CR
BDC	4.17	0.77	0.96	0.97	.922										
AC	4.27	0.80	0.93	0.94	.939**	0.866									
PC	4.12	0.83	0.92	0.92	.942**	.798**	0.854								
DSC	4.09	0.81	0.91	0.91	.951**	.854**	.859**	0.812							
OI	3.93	0.91	0.91	0.92	.453**	.412**	.426**	.424**	0.838						
DMS	3.77	0.93	0.93	0.93	.573**	.538**	.507**	.566**	.467**	0.897					
EOA	3.83	0.81	0.90	0.91	.510**	.476**	.443**	.517**	.383**	.577**	0.842				
BVC	3.87	0.86	0.97	0.97	.542**	.529**	.550**	.548**	.458**	.573**	.510**	.961			
SR	3.77	0.93	0.94	0.95	.451**	.440**	.372**	.455**	.471**	.561**	.640**	.926**	0.849		
PO	3.81	0.95	0.93	0.93	.526**	.496**	.453**	.530**	.417**	.585**	.570**	.936**	.798**	0.866	
CR	4.03	0.89	0.95	0.96	.521**	.524**	.414**	.528**	.370**	.510**	.543**	.935**	.784**	.827	0.806

Note: N=185. Square root of the AVEs on diagonal. Each construct of square root of the AVE exceeds the inter-construct correlation for adequate discriminant validity. ** Correlation is significant at the 0.01 level (two-tailed).

BDC: Big data capabilities; AC: Analytical capability; PC: Predictive capability; DSC: Decision support capability; OI: Organizational innovativeness; DMS: Decision making speed; EOA: Extent of analysis; BVC: Business value creation; SR: Supplier relations; PO: Production and operations; CR: Customer relations

BDC and BVC are second-order constructs formed by weighted sums of their first-order constructs

An exploratory factor analysis with varimax rotation for all constructs was conducted to test construct validity. Factor loadings for each construct are shown in Table 3. The results indicate that all items loaded on a distinct construct and their factor loadings were greater than 0.5, showing a good convergent validity. The results confirmed the existence of the two second-order constructs. All with eigenvalues are greater than 1.0, indicating good discriminant validity.

Table 3. Item Loadings and Cross-loadings

Construct	Items	1	2	3	4	5
Analytical capability (AC)	AC_1	.294	**.793**	.038	-.069	.096
	AC_2	.339	**.784**	.080	.058	-.078
	AC_3	.340	**.794**	.032	.071	.017
	AC_4	.265	**.771**	.250	.021	.126
	AC_5	.394	**.687**	.149	.027	.171
Predictive capability (PC)	PC_1	.208	**.773**	.186	.259	.106
	PC_2	.215	**.802**	.188	.181	.014
	PC_3	.088	**.786**	.218	.128	.239
	PC_4	.086	**.724**	.224	.120	.319
Decision support capability (DSC)	DSC_1	.437	**.771**	.069	.144	.028
	DSC_2	.325	**.807**	.172	.114	.008
	DSC_3	.114	**.721**	.199	.250	.339
	DSC_4	.259	**.691**	.080	.146	.311
Organizational innovativeness (OI)	OI_1	.285	.232	**.734**	.205	-.044
	OI_2	.300	.232	**.795**	.076	.062
	OI_3	.268	.093	**.833**	.045	.057
	OI_4	.128	.203	**.796**	.027	.125
	OI_5	.196	.117	**.793**	.037	.136
Decision making speed (DMS)	DMS_1	.384	.354	.169	.212	**.652**
	DMS_2	.426	.375	.183	.173	**.722**
	DMS_3	.398	.391	.174	.177	**.691**
Extent of analysis (EOA)	EOA 1	.411	.212	.126	**.678**	.266
	EOA _2	.432	.276	.131	**.714**	.165
	EOA _3	.303	.319	.173	**.726**	.050
	EOA _4	.377	.294	.206	**.720**	-.109
	SR_1	**.747**	.182	.371	.086	.062

Supplier relations (SR)	SR_2	**.735**	.122	.299	.262	.084
	SR_3	**.655**	.223	.361	.248	.306
	SR_4	**.754**	.235	.253	.177	.099
Production and operations (PO)	PO_1	**.751**	.328	.171	.260	.022
	PO_2	**.761**	.249	.223	.163	-.041
	PO_3	**.660**	.314	.169	.229	.251
Customer relations (CR)	PO_4	**.731**	.292	.231	.239	.191
	CR_1	**.807**	.198	.171	.102	.208
	CR_2	**.760**	.331	.108	.125	.247
	CR_3	**.843**	.276	.122	-.001	.154
	CR_4	**.780**	.345	.121	-.030	.220

Note*:* Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

5 components extracted

We condensed big data capabilities and big data business value creation using latent variable scores of the subscales as items of the higher order construct. We formed the second-order formative construct big data capabilities and tested whether they are highly correlated with their indicators. The result can be found in Figure 4. The exploratory factor analysis in Table 2 also confirms our findings. The second-order construct (big data capabilities in creating business value) was formed by calculating the weights (γ_i) of the first-order constructs to the second-order construct using a principal components factor analysis (Pavlou & El Sawy, 2006):

Big Data Capabilities =

$0.362 \times$ Analytical Capability $+ 0.356 \times$ Predictive Capability $+ 0.283 \times$ Decision Support Capability.

The impact of all (γ_i) first-order constructs on big data capabilities is significant ($p < 0.001$) (See results in Figure 4).

Figure 4. The Second-Order Construct Big Data Capabilities in Creating Business Value

*** Correlation is significant at the 0.001 level (two-tailed); ** Correlation is significant at the 0.01 level (two-tailed).

The second-order reflective construct (big data business value creation) was also evaluated using principal components factor analysis. We also tested the correlations among the first-order constructs, suggesting that the first-order constructs may belong to the same set (Chin 1998). The results in Figure 5 and Table 2 can both confirms our findings.

Big Data Business Value Creation=

$0.339 \times$ Supplier Relations $+ 0.308 \times$ Production & Operations $+ 0.353 \times$ Customer Relations.

The impact of all (γ_i) first-order constructs on big data business value creation is also significant (p < 0.001) (See results in Figure 5).
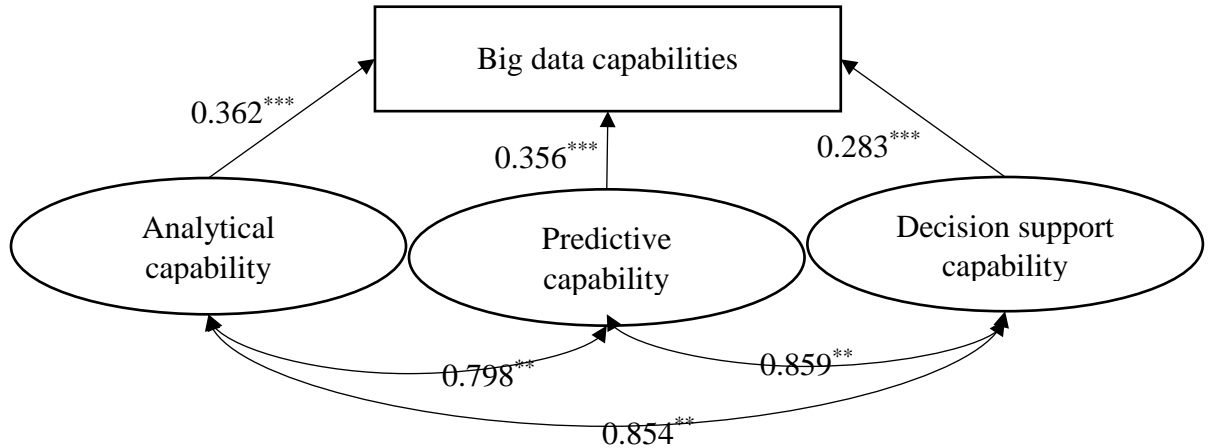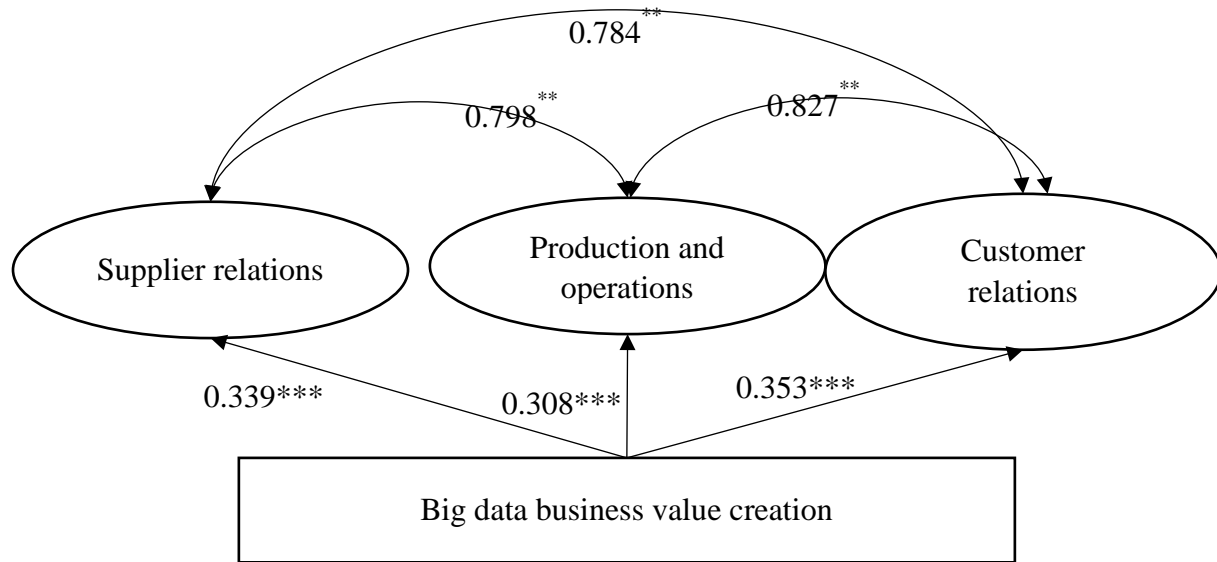

Figure 5. The Second-Order Construct Big Data Business Value Creation

*** Correlation is significant at the 0.001 level (two-tailed); ** Correlation is significant at the 0.01 level (two-tailed).

Structural Model Assessment

The proposed research model was tested using SmartPLS Graph 2.0, which can handle small sample data and moderating effects (Gefen & Straub, 2000). The path coefficients and explained variances of the structural model are shown in Figure 2. The significance levels were evaluated with 200 bootstrap runs. As SmartPLS does not generate the model fit statistics, we only use R squares to report the explanatory power of the structural model. The structural modeling results can be found in Figure 6.

Figure 6. Structural Modeling Results

Note: *p<0.05, **p<0.01, ***p<0.001, n.s.=Not significant.

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Hypotheses Testing

The first two hypotheses (H1a and H1b) state that big data capabilities will positively influence both the speed and extent of organizational decision-making. As shown in Table 4, the paths from big data capabilities to decision-making speed ($\beta=0.456$, $p<0.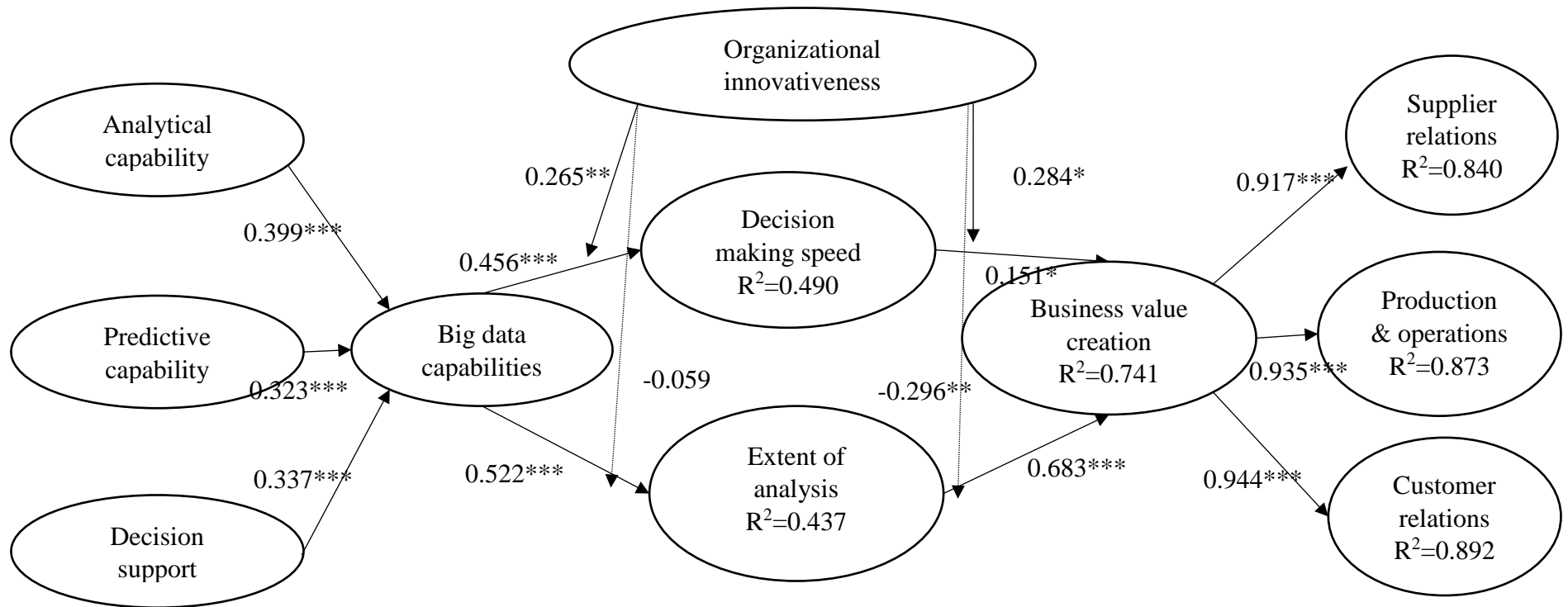001$) and extent ($\beta=0.522$, $p<0.001$) are both significant. Thus, our results support these two hypotheses. The next hypotheses state that decision making speed and extent will positively influence business value creation. As demonstrated below, while the path from speed to business value creation is significant ($\beta=0.151$, $p=0.034$) as hypothesized, the path from analysis extent to business value creation is not significant ($\beta=0.683$, $p<0.001$). Hence, hypothesis 2 is supported but hypothesis 3 is rejected.

Hypothesis 4 states that organizational innovativeness will moderate the effect between big data capabilities and organizational decision-making. Hypotheses 5 states that organizational innovativeness will moderate the effect between organizational decision-making and business value creation. The path from big data capabilities to decision making speed ($\beta=0.265$, $p=0.005$) moderated by organizational innovativeness is significant; the path from decision making speed to business value creation ($\beta=-0.059$, $p=0.404$) moderated by organizational innovativeness is significant as well. However, the path from data capabilities to decision-making analysis extent ($\beta=0.284$, $p=0.030$) moderated by organizational innovativeness is not significant; the path from decision making analysis extent to business value creation ($\beta=-0.296$, $p=0.024$) moderated by organizational innovativeness is negatively significant. Thus, the findings partially support hypotheses 4 and 5.

Table 4. Structural Modeling Results

Relationships	β	t-Value	p-Value	Conclusion
H1a: BDC → DMS	0.456	4.618	<0.001	H1a supported
H1b: BDC → EOA	0.522	3.804	<0.001	H1b supported
H2: DMS → BVC	0.151	2.131	0.034	H2 supported
H3: EOA → BVC	0.683	6.033	<0.001	H3 supported
H4a: OI: BDC → DMS	0.265	2.832	0.005	H4a supported
H4b: OI: BDC → EOA	-0.059	0.218	0.828	H5a not supported
H5a: OI: DMS → BVC	0.284	2.193	0.030	H4b supported
H5b: OI: EOA → BVC	-0.296	2.279	0.024	H5b negatively supported

Note: *p<0.05, **p<0.01, ***p<0.001.

BDC: Big data capabilities; OI: Organizational innovativeness; DMS: Decision making speed;

EOA: Extent of analysis; BVC: Business value creation

Discussion

Implications for Theory

This study offers a better understanding of optimizing decision-making processes with the help of big data. The model indicates that big data capabilities are the foundations of quality decisions. This is also the requirement of data-driven decision making. The challenge for organizations is to build big data platforms and develop a data driven decision making culture. Resource allocation processes and resource orchestration processes should be reviewed in order to

make better decisions. Investing in more big data related applications and building big data capabilities should be a firm's strategic action in order to build a data-driven organization.

Scholars have pointed out that data itself is not the biggest obstacle; the biggest challenges to adopting analytics are the managerial and cultural aspects (LaValle et al., 2011). Organizational innovativeness in this study has been confirmed to partially moderate the relationship between big data capabilities and big data use outcomes. Organizations with higher organizational innovativeness are more likely to be successful in creating business value. Thus, developing a culture that accepts new technology innovation will enable firms to make better decisions and to create higher business value.

How information technology (IT) creates business value has been a research stream for scholars in the last few decades (Chen et al., 2014). However, few studies have directly tested how big data capabilities affect the organizational decision making process, and in turn business value creation. The lack of empirical literature both hinders research on the value of big data and implementation facilitation of new technology. Scholars call for research of the mechanism and the process of big data adding business value to organizations (Mikalef et al., 2017). This study answers the call and extends the understanding of big data use in creating business value. The mediating role of organizational decision making has been highlighted in this study. The moderating role of organizational innovativeness has also been identified. The new findings of how big data produces business value through these two factors contribute to IS literature regarding the relationship between big data technology and value.

Implications for Practice

Timely processing of large volumes and varieties of information from equipment and machines by IT-enabled supporting, monitoring, and learning systems is required for effective

decisions. Larger volumes of data from production can be collected and analyzed faster with big data technologies than ever before. Using big data increases production throughput or service volumes. Big data facilitates traceability to the machine level and provides operations managers with better visibility. Data analysis results can be used to improve operating flexibility and enhance utilization of machinery and equipment. Productivity of labor can also be improved through this process and business processes and production workflows can be streamlined. Managers who understand how big data capabilities and organization of innovativeness work together to increase business value will be able to create effective, efficient, value-added processes.

The findings in this study offer many insights for big data use across industries. These insights can help organizations enhance value creation chains in the era of big data. For example, in the supply chain area, use of big data can help improve monitoring of the quality of products and services from suppliers. Big data analysis results can provide decision support to select the right suppliers at the first price. Collaborations between firms and suppliers can also be improved because of the advantages that big data bring.

Limitations and Directions for Future Research

There are some limitations to this study. First, the data sample is from the Chinese culture. Country characteristics can shape IT business value (Melville, Kraemer, & Gurbaxani, 2004) and innovativeness may be different across cultures. We encourage future related studies to collect data from developed countries and different cultures.

Second, managers assessed their organizations to answer the questions. Such assessment may be biased. In order to make the measurement more robust, these constructs could be collected in a more precise way. For example, the customer relations could be measured by customers' response or feedback.

Last, we do not investigate all of the aspects of business value creation. Future research should examine other aspects from the process level view.

Conclusion

Using big data to create business value is one challenge for practitioners in the current business environment. Drawing on a process-level business value creation view and the dynamic capabilities perspective, we investigated the use of big data to create business value through organizational decision making quality improvement. The results indicate that big data capabilities have a positive impact on organizational decision making, and then business value creation. The moderating role of organizational innovativeness has also been shown to partially moderate big data capabilities, organizational decision making, and business value creations. The findings from this study contribute to both theory and practice.

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APPENDIX 4: Measurement items

Big data capability (Newly developed) (1 = strongly disagree; 5 = strongly agree)

Please specify the extent to which you agree or disagree with the following statements:

Analytics capability (Newly developed)

1. Big data has helped our company analyze structured data (e.g., transaction data, financial data, etc.).

2. Big data has helped our company analyze unstructured data (e.g., customer reviews, social media data, website clickstreams data, etc.).

3. Big data has enabled our company to analyze high volumes of data.

4. Big data has helped our company uncover previously unseen patterns by data analysis.

5. Big data has allowed our company to conduct fast speed analysis.

Predictive capability (Newly developed)

1. Big data has enabled our company to improve the accuracy of predictions.

2. Big data has helped our company identify trends to make predictions in different areas (e.g., customer behaviors, marketing, product development, etc.)

3. Big data enables our company to improve the effectiveness of predictions.

4. Big data has allowed our company to make good real-time predictions.

Decision support capability (Newly developed)

1. Big data has helped our company support strategic, managerial, and operational decision-making that benefit a broad range of functions.

2. Big data has enabled a better business decision making.

3. Big data has supported our company to make real-time decisions.

4. Big data has enabled our company to move to data-driven decision-making.

Organizational innovativeness (adapted from Venkatesh and Bala, 2012) (1 = strongly disagree; 5 = strongly agree)

Please specify the extent to which you agree or disagree with the following statements:

1. My organization readily accepts innovations based on research results.

2. Management in my organization actively seeks innovative ideas.

3. Innovation is readily accepted in this organization.

4. People are penalized for new ideas that don't work. (R)

5. Innovation in this organization is perceived as too risky and is resisted. (R)

Organizational decision making (adapted from Leidner, Carlsson, Elam, & Corrales, 1999; Leidner and Elam, 1993) (1 = To No Extent; 5 = To a Great Extent)

To what extent has big data helped you do the following…

Decision-making speed

1. Identify potential problems faster.

2. Sense key factors impacting my area of responsibility.

3. Notice potential problems before they become serious crises.

The extent of analysis

1. Spend significantly more time analyzing data before making a decision.

2. Examine more alternatives in decision making.

3. Use more sources of information in decision making.

4. Engage in more indepth analysis.

Big data business value creation (adapted from Tallon, 2011) (1 = strongly disagree; 5 = strongly agree)

Please specify the extent to which you agree or disagree with the following statements: We believe big data is

Supplier relations

1. Helping my corporation gain leverage over its suppliers.

2. Reducing variance in supplier lead times.

3. Helping develop close relationships with suppliers.

4. Improving monitoring of the quality of products and services from suppliers.

Production and operations

1. Improving production throughput or service volumes.

2. Improving operating flexibility.

3. Enhancing utilization of machinery and equipment.

4. Improving the productivity of labor.

5. Streamlining business processes.

Customer relations

1. Enhancing your ability to provide after-sales service and support.

2. Improving product/service distribution.

3. Enhancing flexibility and responsiveness to customer needs

4. Enhancing your ability to attract and retain customers.

5. Enabling you to support customers during the sales process.

Note: (R) = Reverse scored.

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INFORMED CONSENT
for a Research Study entitled
"Big Data Capabilities, Decision-making Impact, and Business Value Creation"

Principle Investigator: Shiwei Sun – PhD student at Department of Aviation& Supply Chain Management, Harbert College of Business, Auburn University

Purpose of the Study: The purpose of this research study is to test the relationships among big data capabilities, decision-making impact, and business value creation.

Procedure: The survey focuses on your perceptions of and attitudes toward big data capability. Survey items ask you to indicate the degree to which you agree with a series of statements. Please read relevant background information, and answer survey questions/items based on your organization's practice, by marking the appropriate options in the survey. The approximate total time to complete the questionnaires should be about 10-15 minutes.

Confidentiality: You are selected to be participants, based on your business background and your understanding of big data. The survey is for research purpose only. At all times, your privacy will be respected. At no time will individual identifying information be provided to outside sources unless required by law.

Expected Risks: There are no foreseeable risks to you by completing this survey, as all results will be kept completely confidential.

Expected Benefits: No direct benefit for your response.

Voluntary Participation: Participation in this study is voluntary. You may choose not to participate without negative consequences. If you do decide to participate, you can change your mind at any time and withdraw from the study without negative consequences. Your decision whether or not to participate will not jeopardize your future relations with Ocean University of China and/or Auburn University, or your grade in class.

Use of Research Results: Results may be presented at research conferences and in scientific publications by the principal investigator. Results will be presented in aggregate form only. No names or individually identifying information will be revealed.

Future Questions: If you have any questions concerning your participation in this study now or in the future, you can contact the **principal investigator, Shiwei Sun**, at 334-444-4000 or via e-mail szs0100@auburn.edu

Consent to Participate: I have read or had read to me all of the above information about this research study, including the research procedures, possible risks, side effects, and the likelihood of any benefit to me. The content and meaning of this information has been explained and I understand. All my questions, at this time, have been answered. I hereby consent and do voluntarily offer to follow the study requirements and take part in the study.

If you have questions about your rights as a research participant, you may contact the Auburn University Office of Research Compliance or the Institutional Review Board by phone (334)-844-5966 or e-mail at IRBadmin@auburn.edu or IRBChair@auburn.edu.

HAVING READ THE INFORMATION PROVIDED, YOU MUST DECIDE WHETHER OR NOT YOU WISH TO PARTICIPATE IN THIS RESEARCH STUDY. YOUR SIGNATURE INDICATES YOUR WILLINGNESS TO PARTICIPATE.

_____   _____

Participant's signature   Date   Investigator   Shiwei Sun,   Date

_____

Printed Name