Essays on Exploring the Value of Business Analytics in Health Care

by

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Abstract

Although researchers and practitioners across various disciplines, including computer science, healthcare informatics, and clinical medicine have advocated that business analytics have tremendous benefits for healthcare industries, extant research has paid insufficient attention on the exploration of its business value. The series of essays in this dissertation strive to close this knowledge gap.

Essay 1 develops a generic IT-enabled transformation model based on resource-based theory and practice-based view. This model reveals the causal relationships among IT capability, IT-enabled transformation practice, benefit dimensions and business value. This proposed model is tested by analyzing secondary data consisting of big data analytics implementation cases in the healthcare context. Through analyzing these cases, this study seeks to understand better how healthcare organizations can leverage big data analytics for improving clinical practices and creating business value. In addition to conceptually defining four big data analytics capabilities, this model also identified three significant path-to-value chains which offer some insights regarding theoretical and managerial implications

Essay 2 investigates whether organizations' decision making effectiveness can be influenced by the use of business analytics systems. Specifically, this works develops a research model to examine the mechanisms by which business analytics capabilities (i.e., effective use of data warehouse tools, effective use of analytics tools, and effective use of data visualization tools) in healthcare units are shown to indirectly influence decision-making effectiveness through a mediating role of absorptive capacity. This study employed a survey method to collect primary data from Taiwan's healthcare industry. Structural equation modeling (SEM) was used for path

analysis. This study conceptualizes, operationalizes, and measures the business analytics (BA) capability as a multi-dimensional construct formed by capturing the functionalities of BA systems in healthcare. The result found that healthcare units are likely to obtain valuable knowledge as they utilize the data interpretation tools effectively. Also, the results show that the effective use of data analysis and interpretation tools in healthcare units indirectly influence decision-making effectiveness, an impact that is mediated by absorptive capacity.

Essay 3 proposes a novel research model drawing on configuration view for the determination of business analytics-enabled business value. We examine how big data analytics capabilities interact with complementary organizational resources and organizational capabilities into multiple configurations to achieve quality of care and financial performance in hospital settings. To account for the holistic, equifinal, and complex interactions among business analytics elements needed to achieve business value, this study employs a relatively new approach termed fuzzy-set qualitative comparative analysis (fsQCA) that go beyond simple linear additive (or multiplicative) effects. The findings from fsQCA advance our understanding of how big data analytics-enabled IT capabilities combine with other organizational elements to achieve quality of care in health care. Most importantly, we offer evidence that different solutions leading to the same quality of care performance from the effective use of big data analytics and other organizational elements do exist.

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List of Abbreviations

BA	Business analytics
BVIT	Business value of information technology
RBT	Resource-based theory
PBV	Practice-based view
EHRs	Electronic health records
PLS	Partial least squares
SEM	Structural equation modeling
fsQCA	Fuzzy-set qualitative comparative analysis

ESSAY 1: An Integrated Big Data Analytics-Enabled Transformation Model: Application to Healthcare

Introduction

Constant increasing large volume of data in various formats from electronic health records (EHRs) and sensors as well as other external sources such as social media, pharmaceutical events, insurance claims/billing, and R&D laboratories, is challenging healthcare organization's data management capabilities and clinical practices (Ferranti et al., 2010; Raghupathi & Raghupathi, 2014; Ward, Marsolo, & Froehle, 2014). Needs for high quality data is not unique for healthcare but more vital because it concerns patients' well-being, which is more than a bottom line in other industries. In healthcare, quality data could facilitate reliable predictions of patient behavior, medical knowledge creation, and clinical practice improvements (Kallinikos & Tempini, 2014; Foshay & Kuziemsky, 2014; Oborn, Barrett, & Davidson, 2011). However, poor data quality in the healthcare systems contribute to issues such as billing errors, intentional frauds, or medical mistakes generating more than 50 percent of the unnecessary costs (Ghosh & Scott, 2011). Many care providers are suffering from the lack of data standards and data integration, data overload issues, and barriers to the collection of high-quality data (Ashrafi, Kelleher, & Kuilboer, 2014; Garrido et al., 2014; Shah & Patak, 2014; Ward et al., 2014). Moreover, 80% of health data is untouched because they are semi-structured or unstructured data which continue to grow rapidly and make up a massive part of health data (Murdoch & Detsky, 2013; Russom, 2011). Such data cannot be stored in relational databases or analyzed using traditional statistical methods to extract quality data or information (Işık et al., 2013; Murdoch & Detsky, 2013; Schouten, 2013).

With the promise of greatly improving data quality and enhancing organizational performance, big data analytics, the most influential IT innovations in the last decade, has been embraced by many healthcare organizations worldwide (Murdoch & Detsky, 2013). Medical professionals urge their peer institutions to leverage the new collection and analysis approaches for gaining a holistic understanding of health from patient data that goes beyond the current state of knowledge about particular diseases (Kallinikos & Tempini, 2014). Big data analytics also provides solutions to fill the growing need of healthcare managers to manage the surge of unstructured clinical data, make better use of real-time data, unify all patients' medical records, and capture visual data from devices, thus supporting evidence-based medical practice (Angus, 2015; Bates et al., 2003) and improving quality and efficiency of health care delivery (Ghosh & Scoot, 2011; Murdoch & Detsky, 201; Raghupathi & Raghupathi, 2014; Schroeck et al. 2012). Healthcare professionals advocate the urgencies and advantages of adopting big data analytics due to its "… potential to create an observational evidence base for clinical questions that would otherwise not be possible and may be especially helpful with issues of generalizability" (Murdoch & Detsky, 2013, p.135), and it could "..significantly increase profitability and operating efficiencies (Schouten, 2013, p. 42).

However, healthcare industry lags behind the curve of adopting thoughtful analytic approaches (Ferranti et al., 2010; Fihn et al., 2014). A couple of huge impediments have been preventing healthcare organizations to fully embrace big data analytics. First, although an increasing number of healthcare organizations are demonstrating the potential of big data analytics that provides tailored, context-sensitive information to guide clinical practice, only 16 percent of healthcare organizations have substantial experience using analytics across a broad range of functions (Cortada et al., 2012). Much of the rich EHR data set is currently perceived as a by-product of health care delivery, rather than a central asset source for competitive advantages (Murdoch & Detsky, 2013, p.1351). Without business case justifications, it is harder for health care managers to alter their mindset to learn and adopt "new" disruptive technology since they have not been sufficient evidence of big data analytics investment benefits (Murdoch & Detsky, 2013; Shah & Patak, 2014).

Second, big data analytics systems can be an expensive and risky undertaking due to the requirement of conjoint engagement of several healthcare stakeholders (Watson, 2014). A typical big data project costs approximately $9.3 million for building and maintaining Hadoop systems in a 5-year period (Winter, Gilbert, & Davis, 2013). Given the amount of considerable investment on big data analytics yet its contribution to business value remains vaguely understood, it is hard for manager to make their case in spending.

Third, despite the number of big data analytics success models (See Appendix A), they are generic and do not meet the industry particular requirements that are specifically tailored for healthcare domain (Brooks, El-Gayar, & Sarnikar, 2015; Foshay & Kuziemsky, 2014). When evaluating big data analytics in the context of a healthcare domain, it is important to understand how it may impact clinical practices so that it will help develop appropriate models to meet the complexities of this domain (Gastaldi, Pietrosi, & Corso, 2014) which has not been addressed to date in the literature.

The constantly growing body of academic research on big data analytics is mostly technology oriented (see a systemic review of big data research from Wamba, Akter, Edwards, Chopin, & Gnanzou, 2015). There is a urgently need to shift the focus to examine and present the managerial, economic, and strategic impacts of big data analytics and explore the potential business value from the effective use of big data analysis. As IS researchers examining business value of IT, we attempt to further theory and to have practical impacts by addressing this research question: *How does big data analytics contributes to business value for healthcare organizations?*

By addressing this question, this current study contributes to both theory and practice. First, it offers a strategic view of big data analytics by developing a conceptual model of Big Data Analytics Enabled Transformation (BDET), where the concept of resource based view, IT-enabled transformation (Venkatraman, 1994) and practice -based view (Bromiley & Rau, 2014) are used to link the big data analytics capabilities to IT-enabled transformation practices and to a potential benefits and performance framework. Secondly, BDET model is then applied to the healthcare context to provide guidance and evidences for healthcare organization managers for their business case justifications.

The remainder of this paper is structured as follows: the next section, Current State of Big Data Analytics Research with two sub-sections, Big Data Analytics as Information Technology Architecture and Business Value of Big Data Analytics, serves as our literature review and theoretical foundation; followed by our conceptual model, after which the research method, findings and discussions, contributions to research, implications for practice and recommendations, then limitations and future research directions are discussed as our conclusion.

Current State of Big Data Analytics Research

Big data analytics is increasingly advocated as one of the most important strategic IT investments for healthcare organizations. Even though scholarly research has reported on the potential of harvesting data-driven insights, supporting evidence-based medicine, and improving quality of care at a lower cost (Gillon et al., 2014; Groves, Kayyali, Knott, & Kuiken, 2013;

Schneeweiss, 2014; Raghupathi & Raghupathi, 2014; Ward et al., 2014), most healthcare practitioners are still struggling to make progress with big data analytics as in understanding the technology and making their business cases for the expenses. This prompts us to firstly provide an easy-to-understand presentation of big data analytics architecture, its components and functionalities for non-technical researchers and practitioners to have an overall view without of big data analytics. Then we will review prior investigations of its business values.

Big Data Analytics as Information Technology Architecture

A big data analytics system comprises an integrated array of aggregation techniques, analytics techniques (e.g., descriptive analytics and predictive analytics), and interpretation techniques that allow users to transform data into evidence-based decisions and informed actions (Cao et al., 2015; Davenport & Harris, 2007; Jagadish et al., 2014). Building on the view of big data analytics as an IT architecture, in turn, researchers agree that it is then characterized by a set of distinct IT architectural components (Chan, 2014; Jagadish et al., 2014; Watson, 2014). We identify the architectural components of big data analytics from its tools and functionalities by reviewing the relevant academic literature (e.g., Raghupathi & Raghupathi, 2014; Ward et al., 2014) and technology tutorials (e.g., Hu et al., 2014; Watson, 2014). These studies develop big data analytics architecture on the concept of information lifecycle management (Kung et al., 2015; Storage Networking Industry Association, 2009). In general, data regardless of its structure in a system follows this lifecycle, starting with collection, through repository and process, and ending up with dissemination of data. This concept helps researchers to understand all the phases of information life cycle in business analytics architecture (Jagadish et al. 2014; Kung et al., 2015). With this view, big data analytics architecture we present here is loosely comprised of three major architectural components described below: data aggregation, data analysis, and data interpretation.

Data aggregation

The first architectural component is *data aggregation*, which aims to collect heterogeneous data from multiple sources and transforming various sources data into certain data formats that can be read and analyzed (Ward et al., 2014). In this component, data will be intelligently aggregated by three key functionalities from data aggregation tools: acquisition, transformation, and storage (Raghupathi & Raghupathi, 2014). First, data acquisition is used to effectively collect and extract data from external sources and all the health system's components throughout the healthcare units (Phillips-Wren et al., 2015). Second, during data transformation, transformation engines are capable of moving, cleaning, splitting, translating, merging, sorting, and validating data. These transformation engines make data consistent, visible and easily accessible for analysis. Put in healthcare context, data such as that typically contained in a patient record would be extracted from EHR systems and subsequently converted into a specific standard data format, sorted by the specified criterion (e.g., patient name, location, or medical history), and then the record is validated against data quality rules (Cha, Abusharekh, & Abidi, 2015). Finally, the "cleaned" data are loaded into the target databases such as Hadoop distributed file systems (HDFS) or in a Hadoop cloud for further processing and analysis. The data storage principles are based on compliance regulations, data policies and access controls, and data storage methods can be implemented and completed in batch processes or in real time.

Data analysis

The second architectural component, *data analysis*, aims to process all kinds of data and perform appropriate analyses for harvesting insights (Wald et al., 2014). This is particularly important for transforming patient data into meaningful information that supports evidence-based decision making and meaningful use practices for healthcare organizations. In simple taxonomy of analytics developed by Delen (2014) there are three main kinds of analytics: descriptive, predictive, and prescriptive analytics, each distinguished by the type of data and the purpose of the analysis.

Descriptive analytics has been widely used in both business intelligence systems and big data analytics systems (Watson, 2014). The methods and algorithms for descriptive analytics such as online analytics processing (OLAP) reporting, excel-based business intelligence application, and data mining support the analysis of structured data within the relational data warehouse that provides the ability to describe the data in summary form for exploratory insights and answer "What has happened in the past?" questions for managers (Phillips-Wren et al., 2015; Watson, 2014). In hospital settings, descriptive analytics is useful because it allows healthcare practitioners to understand past patient behaviors and how these behaviors might affect outcomes from their EHR database. It also provides high-speed parallel processing, scalability, and optimization features geared toward big data analytics, and offers a private and secure environment for confidential patient records (Wang et al., 2015). For example, a Dutch long-term care institution visualizes the number of incidents, the location of incidents occurred, and the type of physical damage by mining a collection of 5,692 incidents at a certain time (Spruit et al., 2014). Frequency tables displayed in visual dashboards enable Dutch long-term care institution to improve their patient safety in the hospital areas.

Predictive analytics allows users to predict or forecast the future for a specific variable based on the estimation of probability (Phillips-Wren et al., 2015; Watson, 2014). Hadoop/MapReduce is one of the most commonly used predictive analytics-based software product which integrates the analytical approaches such as natural language processing (NLP), text mining, and natural networks in a massively parallel processing (MPP) environment. In general, predictive analytics provides the ability to process large volumes of data in batch form cost-effectively, allowing the analysis of both unstructured and structured data as well as supporting data processing in near real time or real time (Belle et al., 2015). More importantly, predictive analytics enables users to develop predictive models in a flexible and interactive manner to identity causalities, patterns and hidden relationships between the target variables for future predictions. Applying it to healthcare context, predictive analytics helps managers disentangle the complex structure of clinical cost, identify best clinical practices, and gain a broader understanding of future healthcare trends based on knowledge of patients' lifestyles, habits, disease management and surveillance (Groves et al., 2013). For example, predictive analytics supports Beth Israel Deaconess Medical Center's home health care by predicting patient illness, quickly deploying nurse to supplement the care no matter where the patient suffers a health emergency, avoiding expensive emergency department visits, and collaborating with local healthcare providers for care coordination (Halamka, 2014). Similarly, the Hospital for Sick Children finds that predictive analytics can respond to unexpected events by tracking patient data in motion as they happen, and quickly determine next-best decisions (Blount et al., 2010).

Prescriptive analytics is a relatively new kind of analytics, which uses a combination of optimization-, simulation-, and heuristics-based predictive modeling technique such as business rules, algorithms, machine learning and computational modeling procedures (Delen, 2014). Whereas predictive analytics suggests "what will occur in the future (Watson, 2014, p. 1251)," prescriptive analytics offers the optimal solutions or possible courses of actions to help users understand what to do in the future (Phillips-Wren et al., 2015; Watson, 2014). Prescriptive analytics can continually re-predict and automatically improve prediction accuracy by taking in new datasets (a combination of structured, unstructured data and business rule) to aid decision makers in solving problems (Riabacke et al., 2012).

Data interpretation

The third architectural component is *data interpretation*. This component generates outputs such as various visualization reports, real-time information monitoring, and meaningful business insights derived from the analytics components to users in the organization. Three key functionalities are included. The first functionality yields general clinical summaries such as historical reporting, statistical analyses, and time series comparisons. Such reporting can be utilized to provide a comprehensive view to support the implementation of evidence-based medicine (Ghosh & Scott, 2011), to detect advanced warnings for disease surveillance (Jardine et al., 2014), and to guide diagnostic and treatment decisions (Fihn et al., 2014). Second, data visualization, a critical big data analytics feature tends to extrapolate meaning from external data and perform visualization of the information (e.g., interactive dashboards and charts). In healthcare, these visualization reports support physicians and nurses' daily operations and help them to make faster, better evidence-based decisions (Roski et al., 2014). Third, real-time reporting, such as alerts and proactive notifications, real time data navigation, and operational key performance indicators (KPIs) can be sent to interested users or made available in the form of dashboards in real time.

Business Value of Big Data Analytics

To unveil the role of big data analytics in creating business value, lately there have been a number of studies focused on developing big data analytics enabled business value models that are generally grounded on information processing view, resource-based theory, and dynamic capability view.

From an information processing view (IPV), big data analytics can be viewed as an effective approach to process a great amount of data to gain reliable information, and transform information into actionable insights and decisions (Cao et al., 2015; Kowalczyk & Buxmann, 2014; Trkman et al., 2010). To facilitate decision-making quality, organizations should design their organizational structure, mechanism, and business processes in conjunction with data analysis processes that may reduce the environmental uncertainty and ambiguity of the problem context (Kowalczyk & Buxmann, 2014; Sharma et al., 2014). In the context of supply chain, for example, Trkman et al. (2010) have indicated that firms that have the ability to analyze and utilize their information within the different stages of the supply chain (i.e., plan, source, make, and deliver) results in superior supply chain performance. Cao and colleagues (2015) further find that business analytics use will influence information processing capability through a mediation of data-driven environment which in turn has a positive effect on decision-making effectiveness. IPV allows researchers to understand how business decisions are made by the joint effect of big data analytics and information processing mechanism. However, these studies mostly focus on exploiting the use of information to improve decision-making processes and outcomes, missing the discussion on what capabilities can be created from the use of big data analytics that organizations should acquire to succeed in driving business value (Phillips-Wren et al., 2015).

Grounded on the theoretical lens of the resource based view (RBV), several studies argue that a firm's unique big data analytics capability can be constructed by the available big data analytics technological resources (e.g., Chae et al., 2014; Kwon et al., 2014; LaValle et al., 2011; Wixom et al., 2013) or the synergetic combination of valuable, rare, imperfectly imitable and non-substitutable organizational resources (e.g., Işık et al., 2013; Seddon et al., 2012; Tamm et al, 2013). For example, Wixom et al. (2013) have identified two key big data analytics capabilities – speed to insight and pervasive use – and their underlying dimension from big data analytics resources for maximizing business value in the fashion retail industry. In addition to the analytics technological capabilities, analytics personnel (e.g., analytical executives, analytical professionals, and analytics employees) (Seddon et al., 2012; Tamm et al, 2013) is also unique big data analytics enabled capability for enhancing organizational performance. However, an ongoing debate in the IS literature is whether IT-enabled constructs specifically for IT resource confer or facilitate competitive advantage directly or indirectly (Devaraj & Kohli, 2003; Wade & Hulland, 2004). Business value of IT literature emphasizes IT resource alone does not unequivocally facilitate competitive advantage (El Sawy et al., 2010). Moreover, strategic management scholars criticize the weakness of RBV in elucidating the missing link in the relationship between the resource-based constructs and organizational performance (Bromiley & Rau 2014; Melville et al., 2004).

To complement the pitfalls of RBV, dynamic capability view has been widely applied to understand the missing link between IT impact and competitive advantage (Pavlou & El Sawy, 2006). In big data analytics research, several studies use dynamic capability to explain how organizations obtain a sustainable competitive advantage from use of their big data analytics through their specific organizational capabilities and learning mechanisms (e.g., Erevelles et al., 2016; Knabke & Olbrich, 2015; Shanks & Bekmamedova, 2012). Most recently, Erevelles et al. (2016) propose a resource-based theory of big data enabled competitive advantage model which not only argues that organizational resources enable firms to transform marketing data into consumer insights, but also underscores that dynamic and adaptive capabilities will be triggered by these insights, thereby creating marketing value. Those studies grounded on the integration of RBV and dynamic capability view generally conclude that firms are mostly like to have the ability to aware information needs and uncover more hidden insights when firms embrace analytical techniques in analyzing their big data. Dynamic capability view helps existing literature to explain the pivotal role of dynamic capability, triggered by big data analytics' potential impacts, on business value. However, IS strategy researchers critique that dynamic capability view may lack a practice lens, resulted in its incapability of providing in-depth insights for the practitioners on why and how they should use IT tools in their organizational practices (Arvidsson et al., 2014; Huang et al., 2014; Orlikowski, 2000; Whittington, 2014).

Practice-based view (PBV) emerging from strategic management has the potential to fuel the next jump in the understanding of business value of IT (Arvidsson et al., 2014; Huang et al., 2014; Orlikowski, 2000; Whittington, 2014). PBV aims to explain the effects of macro-level firm behaviors or characteristics within a practice (Bromiley & Rau, 2014). Adopting a PBV focus not only enables researchers to study how the firm implements organizational practices through the proposed explanatory variables, but also helps develop a deeper understanding of which practices are actually needed for performance in a given context (Bromiley & Rau, 2014). In the specific context of health care, many scholars have adopted a practice lens to provide in-depth insights to healthcare practitioners on how IT tools can be used in improving clinical practices (Azad & King, 2008; Bjørn et al., 2009; Boulus & Bjørn 2008; Jensen & Aanestad 2007; Oborn et al., 2011). In the big data research, a number of studies have explored the value of big data analytics on clinical practices by means of single or multiple case studies (e.g., Bates et al., 2014; Foshay & Kuziemsky, 2014; Halamka 2014; Srinivasan & Arunasalam, 2013). Although these studies could offer practical insights for helping healthcare organizations scope their big data analytics initiatives, their findings have not been collected in a comprehensive framework, or validated on a broader empirical basis.

As no one single theory covers all aspects, we attempt to integrate the well-established, the resource based view, and the more practical based and relatively new one, the practice based view, to build our model. In the next section, we will present our theoretical model and describe the components.

Theoretical Model

The foundation of our theoretical framework comprises of two elements: resource based view and practice base view (See Figure 1). We first build on the resource based view and IT capability literature (Barney, 1991; Barney et al., 2001; Bharadwaj, 2000; Doherty & Terry, 2009; Karimi et al., 2007; Santhanam & Hartono, 2003; Mata et al., 1995) by arguing that big data analytics resources – that is, its big data analytics architectural components (i.e., data aggregation, data analysis, and data interpretation) can create big data analytics-specific capabilities. Drawing on the logic of RBV, big data analytics resources represent the technological sources of big data analytics' business value. In other words, big data analytics capability can be created or reinforced through the application of its three architectural components.

We then follow PBV to explain the effects of macro-level firm behaviors or characteristics on specific outcomes (Bromiley & Rau, 2014). Recently, a theoretical framework with PBV that proposed by Bromiley and Rau (2014) demonstrates how different performances are manifested in firms' execution of various practices that are facilitated by explanatory factors. This framework incorporates a process path of explanatory variables (the enablers of practices), practices, intermediate outcomes, and performance. In this framework, practice, "a defined activity or a set of activities that a variety of firms might execute" (Bromiley & Rau 2014, p. 1249), is a central part of this view. Practice can be treated as the combination of the subject, the action, the tools and the context (Russo-Spena & Mele 2012) or as a set of activities, routines and material arrangements (Schatzki, 2001; 2005). The use of practice itself is important for the outcomes (i.e., intermediate outcomes and firm performance) (Bloom et al., 2013; Giannopoulou et al., 2014; Igira, 2008; Tallman & Chacar, 2011). The explanatory variables can be viewed as antecedents or enablers of the practice. However, the explanatory variables are not specified in the Bromiley and Rau's (2014) PBV model, which on the one hand allows for idiosyncratic interpretation, but on the other leaves the applicability debatable.

In this study, the linear progress path of PBV framework is adopted: from the explanatory variables to practices, then to the intermediate outcomes ("benefits" in our model), and finally the organizational performance ("business value" in our model), as shown in Figure 1. Integrating RBV and PBV in big data research context, we select big data analytics capabilities that are driven by big data analytics resources as the explanatory variables of our theoretical model. We also argue that organizational practices have a pivotal role in transforming the big data analytics capabilities into the business value.

In terms of organizational practices, we focus on IT-enabled transformation practices defined as the sequential changes that begin with operational improvement and internal integration through IT functionalities and then through a set of business redesign activities to transform IT capabilities into competitive advantage and financial performance (Dehning et al., 2003; Lucas et al., 2013; Markus & Benjamin, 1997; Venkatraman, 1994).

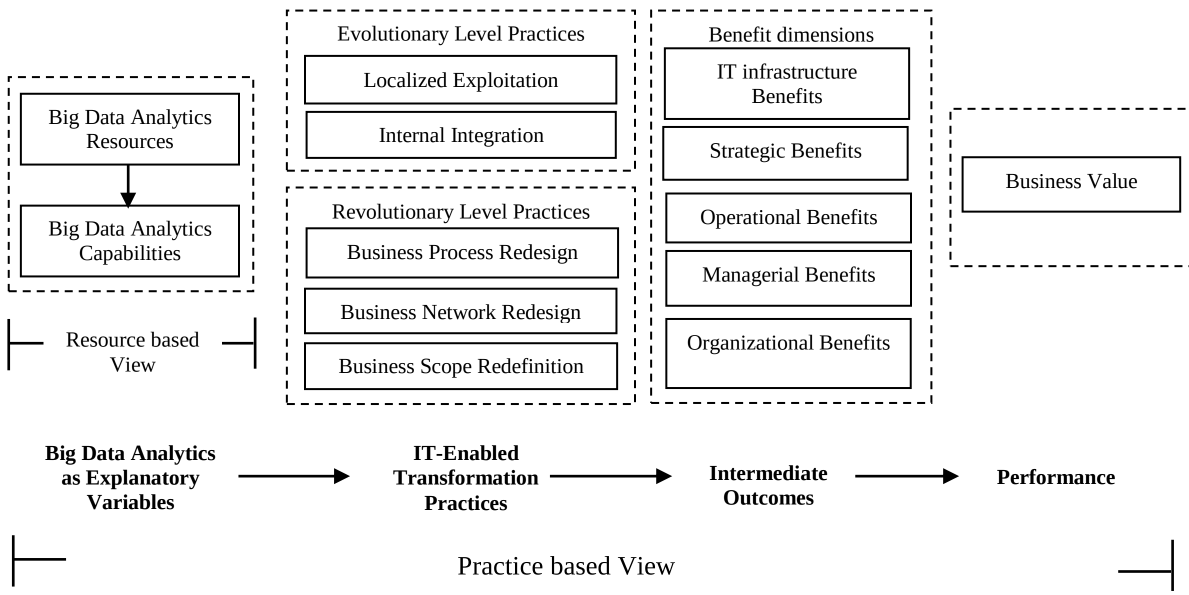


Figure 1. Big Data Analytics-Enabled Transformation Model

We conceptualize IT-enabled transformation practice adopting Venkatraman's (1994) model which identifies a set of organizational change activities executed through IT/IS supports. Venkatraman's (1994) model consists of two levels, evolutionary and revolutionary, which are formed by 2 and 3 practices respectively. Localized exploitation practice refers to "a practice to leverage IT functionality to redesign business operations" (Venkatraman, 1994, p. 82), while internal integration practice refers to “a practice to leverage IT capability to create a seamless organizational process – reflecting both technical interconnectivity and organizational interdependence” (Venkatraman 1994, p. 82). These two formed the evolutionary transformation level practices. Business process redesign practice are “redesigning the key processes to derive organizational capabilities for competing in the future as opposed to simply rectifying current weaknesses” (Venkatraman 1994, p. 82). The business network redesign practice is defined as “articulating the strategic logic to leverage related participants in the business network to provide products and services in the marketplace” (Venkatraman 1994, p. 82), while business scope redefinition practice refers to “a practice that allows organization to redefine the corporate scope that is enabled and facilitated by IT functionality” (Venkatraman 1994, p. 82). These three practices formed the revolutionary transformation level.

In order to conceptualize intermediate outcomes of our model, we adopt a multidimensional IS benefit framework developed by Shang and Seddon (2002). Their framework was built on a large bogy of previous research and presents five benefit dimensions which include IT infrastructure benefits, operational benefits, organizational benefits, managerial benefits, and strategic benefits and aggregates 21 sub-dimensions, as shown in Table 1.

We justify the selection of Shang and Seddon’s benefit dimensions as the outcome of our model with four reasons. First, one component of our research goal is to explore and thus present a specific set of benefit sub-dimensions in big data analytics context. Shang and Seddon’s framework helps us to classify the benefit categories, which, in turn, enhances our understanding of business value. Second, their benefit framework has been refined by many studies related to ERP systems and specific IS architectures (Esteves, 2009; Gefen & Ragowsky, 2005; Mueller et al., 2010). It was designed for managers to assess the benefits of their companies’ enterprise systems, which could be applied as a general model. Third, Shang and Seddon (2002) provide a clear guideline for assessing and classifying benefits from IT architecture. This guide also suggests ways of how to validate the IS benefit framework through implementation cases, which is helpful for our study. Finally, IT infrastructure, operational, and managerial benefits have been reported in some of the existing business analytics studies (e.g., LaValle et al., 2011; Trkman et al., 2010), and strategic benefits such as speed to market, improved business understanding, and reputation have been mentioned in Wixom et al. (2013) study.

Table 1. IS benefit framework

Benefit dimension	Description	Sub-dimensions
IT infrastructure benefits	Sharable and reusable IT resources that provide a foundation for present and future business applications	• Building business flexibility for current and future changes • IT cost reduction • Increased IT infrastructure capability
Operational benefits	The benefits obtained from the improvement of operational activities	• Cost reduction • Cycle time reduction • Productivity improvement • Quality improvement • Customer service improvement
Managerial benefits	The benefits obtained from business management activities which involve allocation and control of the firms' resources, monitoring of operations and supporting of business strategic decisions	• Better resource management • Improved decision making and planning • Performance improvement
Strategic benefits	The benefits obtained from strategic activities which involve long-range planning regarding high-level decisions	• Support for business growth • Support for business alliance • Building for business innovations • Building cost leadership • Generating product differentiation • Building external linkages
Organizational benefits	The benefits arise when the use of an enterprise system benefits an organization in terms of focus, cohesion, learning, and execution of its chosen	• Changing work patterns • Facilitating organizational learning • Empowerment • Building common vision

	strategies.	

Note: adopted from Shang and Seddon (2002)

Research Method

As reflected in our research question, our aim is to conceptualize how the capabilities of big data analytics are created and how the bundling of IT-enabled transformation practices is influenced by big data analytics and thus leads to potential benefits. We approached this research from the perspective of theory for explaining (Gregor, 2006). The main goal of theory for explaining is to provide "an explanation of how, why, and when things happened, relying on varying views of causality and methods for argumentation" (Gregor, 2006, p. 619). It could be one of the best research strategies for inducing a subjective state of understanding in phenomena of interest as carefully taking advantage of research approaches (e.g., interpretive field studies, case studies, and surveys) for explorations (Eisenhardt, 1989; Eisenhardt & Graebner, 2007). Among these research approaches, the case research method is particularly relevant to this study rather than survey methods for two reasons. First, health care industry is lagging behind other industries in adopting big data analytics while the adoption of big data analytics is still at an early stage in general (Shah & Pathak, 2014). As Kohli and Grover (2008) suggested, the better way to increase a broader understanding of how companies' new IT investments payoff is to learn from their success stories and observe their practices. These stories could be a useful materials for the preliminary, exploratory stage of a research issue (Rowley, 2002; Yin, 2000, 2008) and for creating theoretical constructs and propositions (Eisenhardt & Graebner, 2007).

Second, practice based research assumes that practices should be observed, perhaps transformed and mostly studied with qualitative research methods (Huang et al., 2014; Peppard et al., 2014). The case study method could be used to explore a specific phenomenon from an abundant of information and understand how its outcomes occur (Yin, 2008). Therefore, it is appropriate to gather the secondary data from real-world implementation cases to obtain the insights of how big data analytics capabilities and benefits are developed and how organizational practices will be influenced by big data analytics. We decided to take this approach and started our case collection.

Data Collection

One of the major challenges to validate conceptual model from cases is the case selection (Eisenhardt & Graebner, 2007). Several studies have relied on case materials to explore the value of emerging technologies (e.g., Mueller et al., 2010; Seddon et al., 2012; Tiefenbacher & Olbrich, 2015). However, one main common limitation of these studies is that the materials chosen for creating the model are provided from IT vendors and companies and thus may be potentially biased. Usually companies only report on their "success" stories and vendors show case their "success" projects to promote their products. Using such cases will certainly lead to the findings of claimed benefits. To use as little biased materials as possible, we selected cases from academic databases which may provide more rigorous and objective statements.

Our cases were drawn from case material on current and past big data projects from academic databases (i.e., ABI/INFORM Complete, Google Scholar, Web of Science, and IEEE Xplore Digital Library). The following case selection criteria were applied: (1) the case presents a real-world implementation of big data analytics in healthcare; and (2) it clearly describes the big data analytics techniques they introduce, how the techniques affect their clinical practices as well as benefits obtaining from big data analytics. We collected 36 case descriptions and checked against our criteria. Three case descriptions were eliminated, because they are technical case studies which only describe the novel analytics technologies being developed. The final data set consists of 33 case descriptions covering 28 healthcare units or systems that adopted big data analytics (See a list of cases in Appendix B).

Of these cases, 86% (22 cases from the United States; 2 from Canada) are from North America, and 14% are from other regions (1 case each, Australia, China, India, and Netherlands). Forty three percent (12 cases) are "networks/Systems" which means there is a group of hospitals or clinics or research centers for one case. Thirty two percent (9 cases) are single hospitals, 14% (4 cases) government agencies, 7% (2 cases) insurance companies, and one healthcare IT service company. Worthy of noting is that all the 9 hospitals are research/teaching oriented, all are top ranked, and are considered "leader" in their fields. This might play an important role as "early adopters" of big data analytics in healthcare. The similarity among all 28 cases is that they all have affluent funding/revenue.

Research Process and Data Analysis

Our approach is to analyze the statements from case materials that describe the effects big data analytics has on business value in healthcare organizations. Based on the logic of our conceptual model, we specifically studied statements that illustrate (1) How big data analytics capabilities are generated by its functionalities, and (2) whether big data analytics capabilities lead to improvements in the clinical or organizational practices, thereby increasing potential benefits for health care organizations.

Numerous IT business value studies have employed analysis of case descriptions to elaborate business values from the adoption of a specific information system (e.g., Mueller et al., 2010; Peppard, Weill, & Daniel, 2007). For example, Mueller et al. (2010) proposed a service-oriented architecture economic potential model (SOA-EPM) by identifying a set of capabilities (e.g., reusability, interoperability, and flexibility) derived from SOA design principles from SOA implementation projects. In current literature where no big data analytics constructs are formally defined, Mueller et al.'s (2010) approach is particularly suitable for our study to generate categories and subcategories inductively from the case materials, and explore the statement of causality. By coding the statements in the cases, we analyzed statements using our proposed model that builds on the logic depicted in Figure 1. These statements may describe technical solutions, functionalities, potential benefits of a specific business analytics technique, and the ways how practitioners apply it to the specific healthcare services or operations. We treated these statements in the text of the case materials as evidence of support for the patterns in our model. Such patterns could be groups of elements present in a high number of word frequency, connections between a set of these elements, or these elements as a path-to-value chain linking big data analytics and business value. These patterns may help us to gain an understanding of big data analytics' business value in health care.

We generally followed the process provided by Mueller et al. (2010) and took heed of Elo & Kyngäs' (2008) coding process to extract insights from the cases to build our healthcare BDET model.

Preparing for coding process and building an initial model

The first task in this step was to make sense of the coding process in terms of coding unit of analysis, the level of analysis, and the purpose of evaluation (Elo & Kyngäs, 2008). After meeting five times to discuss coding process and model elements, we selected "themes" (informative and persuasive nature of case material) as the coding unit of analysis, which primarily looking for the expressions of an idea that can be sentences, paragraphs, or a portion of a page (Minichiello et al., 1990). The level of analysis in this study is the healthcare organization or system that engages in big data analytics implementation. The purpose of this coding process was to build a big data analytics enabled transformation model for healthcare industry by identifying the critical elements driving business value from big data analytics.

After setting up the coding process, we started to define initial coding for elements in each layer in our model. As aforementioned, the elements for big data analytics resource layer and potential benefit layer are adopted from a set of big data analytics architectural components and the Shang & Seddon's (2002) IS benefit framework, respectively. Our task at this step is to define the elements of the connecting layers, that is, *big data analytics capability* and *IT-enabled transformation practice*. We conducted a literature review on big data analytics as well as healthcare informatics researches. We followed a concept-centric approach suggested by Webster and Watson (2002) and developed our initial list of element coding. For creating the initial element for big data analytics capabilities, we conducted a literature review for a technological understanding of big data analytics as mentioned earlier in Section 2.1. From this review, we fully understand the tools and functionalities provided by big data analytics systems and the nature of big data analytics architectural components. Following the logic of information lifecycle management (Storage Networking Industry Association, 2009) and simple taxonomy of analytics (Delen, 2014), big data analytics capabilities are generated from its architectural components. Delen (2014) further argue that basic analytical capability can be driven by descriptive analytics, while predictive capability can be triggered by predictive and prescriptive analytics. Then we performed a pretest by coding a small portion of case materials and compare/match to the list to validate and also to refine the coding elements (Krippendorff, 2012). After revising several times, four big data analytics capability and six healthcare related practices for the big data capability layer and IT-enabled transformation practice layer are determined respectively.

Coding process

We developed an explicit coding instruction that allows coders to be trained until reaching certain reliability requirements. As suggested by Krippendorff (2012), our coding instruction contains descriptions of the layers and elements of the BDET model (See Table 1 and Appendix C) to ensure coders' understanding of each element (Strauss & Corbin, 1998). We also provided an outline, examples of the coding procedures, and a guideline for using and administering the data sheets for all the coders (Krippendorff, 2012). Some confusions of classification have been addressed by providing the detailed descriptions and examples. For example, for separating the analytical and predictive capabilities, we introduced Delen's (2014) taxonomy of analytics to our coders and provide a list of tools and functionalities for generating these two capabilities as well as the examples obtained from our coding pretest. For helping the coders understand meaningful use of EHR practice, we introduced a summary overview of meaningful use objectives and measures provided by Blumenthal and Tavenner (2010).

To increase the quality of coding process, we recruited two senior consultants in a multinational technology and consulting corporation headquartered in the United States as our expert outside coder panel. Both of them have over 15 years IS-related work experience and are currently consulting several manufacturing companies and hospitals in southeast United States in big data analytics adoption. Using outside coders in the coding process can minimize potential bias of subjective perspectives from the researcher and avoid "self-fulfilling prophecy" issues (Elo & Kyngäs, 2008; Meyer & Goes, 1998). Also, this expert panel can provide rich background knowledge and industrial experience in classifying these statements into the sub-elements of big data analytics capabilities with similar meaning. An Excel table with analysis unit and all the elements listed was given to outside coders to manage the statements extracted from case materials.

One of the expert panel consultants took the first run on selecting statements (the analysis unit) from all 33 case descriptions that illustrate the *path-to-value chain*. He repeated this process once. A statement was selected if it describes how big data analytics contribute to business value. Specifically, the statements had to fully explain: 1) How specific big data analytics tools create big data analytics capabilities, 2) How these big data analytics capabilities help clinical practices, and 3) How these practices can lead to potential benefits in a specific case. This selection of statements served as the base for further analysis.

The selection is given to the other expert; both experts then followed the coding procedure starting with open coding, then axial coding, and finally selective coding (Strauss & Corbin, 1998) to analyze each statement independently. In the open coding process, the coders broke down, examined, and categorized the statements into one of the four layers in our model. The coders also used different color highlights to distinguish each concept relating to the layers and elements. In the axial coding process, the coders reread the statement to explore the connections between the elements, and to develop more precise explanations of what big data analytics architectural components, capabilities, practices, and benefits are, what cause them, and the benefits that arise because of them. In the selective coding, the coders focused more on finalizing the codes (or developing new elements in some cases) by comparing and contrasting other similarly coded elements. We demonstrate this process with two examples in Appendix D and E.

Agreement between these two coders established the path-to-value chains. When there were discrepancies, they reassessed and discussed that particular scenario to see whether an agreement could be achieved. Since some coding words could not be assigned to the initial elements, one new element (i.e., network knowledge creation practice) was subsequently developed. In this coding process, these two coders agreed on 77 % of the categorization resulted in a total of 109 path-to-value chains.

An audit process was carried out to improve the accuracy of classification (Hsieh & Shannon, 2005; Krippendorff, 2004). In the audit process, two of the authors read the statements provided by the expert panel and coded them through the same coding process. The results from the author panel were compared to those from the expert panel. Assessment and discussion were performed by all the authors. A chain was accepted and counted towards the final tally if it was listed on both author and expert panel lists. Overall, the two coding teams agreed on 84% of the classifications. Ensuring interrater reliability led to the elimination of 4 chains after much discussion and debate (Schilling, 2006). The final data set comprises 105 path-to-value chains.

In this study, frequency analysis, a content analytic technique was used to evaluate the importance associated with an element, connection, and chain based on the repeated appearance of statements (Weber, 1990). We present our results of frequency analysis and discuss them in the next section.

Research Results

We present our findings in the following subsections: (1) the total number of occurrences of the elements (i.e., big data analytics architectural layers, big data analytics capabilities, IT-enabled transformation practices and benefits), (2) the distribution of pair-wise connections between the elements in the BDET model, and (3) the distribution of path-to-value chains connecting all the elements describing big data analytics' business value.

Discussion of Elements

Big data analytics architectural layer

In the big data analytics architecture, we find that big data analytics capabilities are mainly obtained from data analysis component (61 occurrences). This is followed by data interpretation component (28) and data aggregation component (16). As we expected, the data analysis component, acts as the center of big data analytics architecture, enables healthcare organizations to explore new insights and optimal solutions based on complex clinical parameters. We break down three big data analytics architectural components as shown in Table 2, which displays the number of occurrence in the case materials for each component. Numerous cases highlight descriptive analysis, OLAP, and data mining as useful tools in big data analytics systems for analyzing structured data from multiple perspectives (e.g., EHRs and activity based historical data) (e.g., Garrido et al., 2014; Kudyba & Gregorio, 2010; Spruit et al., 2014).

Furthermore, our results also show that data interpretation is one of the critical big data analytics features, which permits clinical data to be visualized in a useful way to support physicians and nurses' daily operations and help healthcare managers to make faster, better decisions (Gálvez et al., 2014; Jardine et al., 2014; Ratwani & Fong, 2015). An example is the Department of Health Western Australia who has been collaborating with the Western Australia Drug and Alcohol Office to map and visualize the rates of drug-related hospitalizations, mortality, ambulance callouts, police reported drug-related offences, treatment episodes recorded by drug and alcohol services in the Perth metropolitan area in the HealthTracks system, which assists their governments to identify at-risk populations and areas, and evaluate the association between socioeconomic status and drug-related health outcomes for future service needs (Jardine et al., 2014).

Table 2. Breaking down big data analytics components

Big data analytics components	Tools being used in the cases	The number of occurrence	
Data aggregation	Data warehouse (SQL database, NoSQL database, and cloud-based database)	6	16
	Hadoop distributed file system	6	
	Extract-transform-load (ETL)	4	
Data analysis	Descriptive analysis	18	61
	Online analytic processing (OLAP)	15	
	Data mining	13	
	Text mining/Natural language processing (NLP)	9	
	Predictive modeling	6	
Data interpretation	Visual dashboards/systems	18	28
	Reporting systems/interfaces	10	
Total		105	

Big data analytics capability

The importance of the four types of big data analytics capability are ranked (by frequency count) from our coding (see Table 3). The most important big data analytics capability for healthcare organizations is analytical capability (coded as part of 49 occurrences), followed by decision support capability (26), traceability (16), and predictive capability (14). We find that the ability to process large amounts of clinical data to understand the past and current states of specific target variables (23) is mentioned most often in the analytical capability element. Big data analytics differs from traditional clinical decision support systems because of its unique ability to parallel process large data volumes and parse and visualize data in real time or near real time (Watson, 2014). One case from our collection, a private health insurer in Australia, utilizes comparative analysis to compare current and historical cost and profit data related to healthcare insurance services controlling for claim anomalies, which in turn enabled them in making optimal quotes (Srinivasan & Arunasalam 2013). Our results also show that the ability to explore the causes of occurred medical events from relational databases (14) is one of the important analytical capabilities for healthcare industries. For example, Newark Beth Israel Medical Center (NBIMC) discovered some radiology exam activities as potential causes of longer patient stay by analyzing 43,000 patient cases aggregated from various data sources (Kudyba & Gregorio, 2010). This analytical capability enables NBIMC to improve process efficiency and control costs by identifying the causes of delay in the exam process such as unnecessary extra diagnostic tests and treatments that were previously difficult or impossible to discover.

Table 3. Breaking down four big data analytics capabilities

Big data analytics capabilities	Case examples[1]	The number of occurrence	
Traceability	Integrate seamlessly clinical data across multiple regions or facilities in near real time or real time	8	16
	Track medical events based on the rules that built on hospital claims	5	
	Search clinical databases for all data related to patient characteristics and conditions	3	
Analytical capability	Analyze large amounts of clinical data to understand the past and current state for specific target variables	23	49
	Explore the causes of occurred medical events from relational databases	14	
	Support real-time processing of multiple clinical data streams	12	
Decision support capability	Generate clinical summary (or performance metrics) in real time or near real time and presented in visual dashboards/systems	17	26
	Provide system outputs for role-based decision-making	9	
Predictive capability	Examine undetected correlations, patterns, trends between specific variables of interest across regions or facilities	9	14
	Compare of cross-referencing current and historical data and its outcomes to predict future trends	3	
	Provide actionable insights or recommendations in a format readily understood by its users	2	

Total	105

[1] In order to provide insightful examples, we have rephrased the statements from case studies rather than use direct quotes. This is because the quotes are generally too long and difficult to comprehend. Our expert panel provided rich background knowledge and industrial experience in classifying these statements into the sub-elements of big data analytics capabilities with similar meaning.

Decision support capability generates clinical summary in real time or near real time and presents it using visual dashboards/systems (17) and yields sharable information and knowledge such as historical reports, executive summaries, drill-down queries, statistical analyses, and time series comparisons to different decision makers (9). Some information are deployed in real time (e.g., medical device dashboard metrics) while others (e.g., daily reports) are presented in summary forms. Reports generated by big data analytics engines are distinct from transitional IT architectures as they facilitate the assessment of past and current operational environments across all organizational levels. Visualization reports are normally generated after near-real-time data processing and displayed on healthcare performance dashboards which assist healthcare analysts to recognize emerging healthcare issues such as medical errors, potential patient safety issues and appropriate medication use.

Traceability allows healthcare organizations to track patient data from all their system's IT components and medical devices. Traditional methods for harnessing these data are insufficient due to the volumes which could result in unnecessary redundancy in data transformation and movement and a high rate of inconsistency. Our cases show that big data traceability provides authorized users access to large national or local data pools and integrates data simultaneously from various sources (Bates et al., 2014; Brennan et al., 2014). This not only reduces conflicts between different healthcare sectors, but also decreases the difficulties in linking the data to healthcare workflow for process optimization.

However, despite its importance for healthcare quality improvement, predictive capability only manifested in 14 occurrences. Some (e.g., Srinivasan & Arunasalam, 2013) but not all cases organizations have the ability to discover undetected correlations, patterns, trends between specific variables of interest across regions or facilities. Numerous prior studies indicate that the application of predictive and prescriptive analytics to health care fields is still in its earliest stages (Amarasingham et al., 2014; Bardhan et al., 2015; Shmueli & Koppius, 2010; Spruit et al., 2014). One of our cases demonstrated the difficulty in developing a reliable predictive model without the ability to exploit large quantity of valuable dataset (Spruit et al., 2014). Similarly, Amarasingham et al. (2014) conclude that due to the difficulty to customize legacy healthcare information systems for predictive models it limits the quality of predictions. They further suggest that predictive models may not respond to changes in EHRs, therefore requires IT personnel to manually refine the predictive rules which lowers the efficiency and productivity.

Big Data Analytics Enabled Transformation Practice

Our results reveal that big data analytics capabilities mainly support evidence-based medicine (46), followed by meaningful use of EHR (19), network knowledge creation (12), clinical resource integration (10), multidisciplinary practice (7), network collaborations (6), and personalized care (5). We break down seven IT-enabled transformation practices that are triggered by big data analytics, as Table 4. The majority of statements mention that healthcare systems with the aid of big data analytics can identify practice-based clinical data (e.g., patient demographics, medical history, and treatments) effectively from day-to-day operations and services in clinical settings (16), and abstract insights from systematic literature and research studies (e.g., randomized-controlled trials, clinical guidelines, quasi-experimental studies, and external expert opinions) to build holistic view of evidence (11). These data could be the basis of evidence-based medicine for decision makers as they are transformed into the useful evidence through an evidence quality evaluation (10). For example, MedStar Health, a 10-hospital system serving the mid-Atlantic region in the United States reports that using patient safety event reporting systems (PSRS) resulted in their elimination of many medical errors and produced the guideline for patient safety. Applying visual analytics techniques in PSRS, MedStar aggregates patient safety events across the hospitals and the data from semi-structured interviews to improve awareness of event types and shares event patterns and trends as evidence with department leadership to address potential safety hazards (Ratwani & Fong, 2015).

Meaningful use of EHR is reported as the second highest occurrence of big data analytics enabled transformation practice. An example, reported by Garrido et al (2014), shows that HealthConnect – a big data analytics based EHR system developed for Kaiser Permanente – provides automated reporting of 21 quality measures, resulting in system-wide health care improvements for their patients. One of the reasons that made this automation possible is that their EHR is supported by data mining techniques so data can be captured across conditions, mapped, standardized, and validated effectively.

Overall, our results suggest that a transformation in health care through big data analytics is still in the early stages of evolutionary transformation since 65 of 105 chains were coded into the category of localized exploitation practices (i.e., meaningful use of EHR and evidence-based medicine). Thus, the managerial and strategic benefits are as yet somewhat limited.

Table 4. Breaking down seven big data analytics enabled transformation practices

Big data analytics enabled transformation practices	Case examples	The number of occurrence

Meaningful use of EHR	Useful clinical quality reporting can be generated by EHR systems	8	19
	Generate lists of patients by specific conditions to use for quality improvement, reduction of disparities, research, or outreach	5	
	Maintain up-to-date problem list of current and active diagnoses	4	
	Improve care coordination among healthcare units through an interoperable EHR system	2	
Evidence-based medicine	Identify practice-based evidence from day-to-day clinical operations and services for decision makers	16	46
	Build holistic view of evidence by abstracting insights from literature-based data such as systematic literature sources and research studies	11	
	Overall practice-based and literature-based data are graded to reflect the quality of the supporting evidence	10	
	Explore the fact from patient treatments and medical events to improve a specific outcome	6	
	Patient cases can exchange among providers and patient-authorized entities	3	
Multidisciplinary	Allow physicians to use quality metrics and care dashboards that aggregate information from multidisciplinary teams	4	7
	Provide joint decisions regarding treatments to patients from a multidisciplinary team	3	
Clinical resource integration	Allocate resources to serve each healthcare unit	8	10
	Create centralized information support for clinical operation	2	
Network collaboration	Resolve conflicts on data sources between care providers and other stakeholders	3	6
	Build common understanding of healthcare service between care providers and other stakeholders	3	
Network knowledge creation	Allow all stakeholders to share information on the platforms	7	12
	Discover new knowledge by enabling stakeholders to collaboratively map ideas from interoperable analytic platforms	5	
Personalized care	Create a personalized disease risk profile and disease and wellness management plan for each patent	5	5
Total		105	

Potential benefits of big data analytics

For the third layer of the BDET model, the benefit dimension, our results indicate that the primary utility of IT-enabled practices for healthcare organizations is to enhance their IT infrastructure (44), followed by operational (40), organizational (8), managerial (9), and strategic benefits (4). Breaking down the potential benefits of big data analytics, many cases reveal that big data analytics techniques such as data mining (Kudyba & Gregorio, 2010; Zhang, 2014), visual analytics (Ferranti et al., 2010; Gálvez et al., 2014; Ratwani & Fong, 2015) and predictive analytics (Bardhan et al., 2015; Srinivasan & Arunasalam, 2013) being used to analyze patient data can significantly improve clinical workflow (17), monitor quality, and reduce costs (11).

Moreover, big data analytics has the potential to reduce system redundancy (10) and to transfer data quickly and securely at different locations (7). For example, to aggregate data from about 50,000 patients, 6,700 appointments and medical staff s within the hospitals for building the predictive model to tackle the problem of overbooking appointments, Mental Health Center of Denver use a mining table with 3474 attributes to classify the characteristics of appointment for each patient (Samorani & LaGanga, 2015). This mining table allows recording patient and appointment information accurately and avoiding data duplication in turn to increase predictions quality.

Table 5. Breaking down the potential benefits of big data analytics

Potential benefits of big data	Items	The number of occurrence	
IT infrastructure benefits	Reduce healthcare system redundancy	10	44
	Quickly and securely transfer data between healthcare IT systems at different hospitals	7	
	Reduce maintenance costs regarding data storage	6	
	Avoid unnecessary IT costs	6	
	Better use of healthcare systems	5	
	Conduct basic analytic processing without changes in code	5	
	Gain better IT effectiveness compared to the	3	

	traditional database environments		
	Process standardization among various healthcare IT systems	2	
Operational benefits	Improve workflow efficiency	17	40
	Monitor quality and improve costs and outcomes	11	
	Reduce the time for information extraction from research studies on large databases	8	
	Explore new insights for improving care productivity	4	
Organizational benefits	Improve cross-functional communication and collaboration	5	8
	Solve multidisciplinary problems quickly than traditional manual methods	2	
	Organizational learn from various clinical reports	1	
Managerial benefits	Gain insights quickly about changing healthcare trends in the market	6	9
	Provide members of the board and heads of department with sound information about decision making and planning	3	
Strategic benefits	Building competitive advantage on cost and health service	3	4
	Provide comprehensive view of care delivery for innovation	1	
Total		105	

Discussion of Pair-wise Connections

We further look at the pair-wise connections among the elements that provide us a deeper understanding of (1) how big data analytics capabilities can be generated from big data analytics components (see Table 6), (2) how IT enabled transformation practices can be triggered by big data analytics capabilities (see Table 7), and (3) how big data analytics capabilities contribute to the business value (see Table 8).

Linking big data analytics components with their capabilities

Table 6 provides a technological understanding of how big data analytics capabilities can be created from different big data analytics components. Breaking down theses connections, most obviously, the results show that data analysis component can generate analytical capability (47), while data interpretation component can trigger decision support capability (19).

Table 6. Number of pair-wise connections linking big data analytics components with big data analytics capabilities

Big data analytics capabilities	Big data analytics components			
	Data aggregation	Data analysis	Data interpretation	Total
Traceability	13	3	0	16
Analytical	2	47	0	49
Decision support	1	6	19	26
Predictive	0	5	9	14
Total	16	61	28	105

Linking big data analytics capabilities with transformation practices

Table 7 shows that analytical capability mainly improves evidence-based medicine (27 connections), which in turn can lead to better clinical resource integration (5 connections) and network knowledge creation (5 connections). The second highest count of connections is the link between decision support capability and evidence-based medicine practice, which has 16 links. Our analysis also indicates that increased traceability (15 links) and analytical capability (4 links) play vital roles in improving the meaningful use of EHR practices.

Overall, of the capabilities that are less frequently linked to revolutionary transformation level practices, 9.52% are connected to business process redesign (i.e., clinical resource integration), 17.14% with business network redesign (i.e., network collaboration and network knowledge creation), and 4.76% to business scope redefinition (personalized care). This result agreed with several previous studies (e.g., Hamilton, 2012; Raghupathi & Raghupathi 2014) that the value of big data analytics to healthcare-related operations and services is currently limited since the challenges for health data collection and processing have not been addressed. More advanced applications and maturing analytical processes are needed for big data analytics solutions in healthcare to achieve their full potential.

Table 7. Number of pair-wise connections linking big data analytics capabilities with big data analytics enabled transformation Practice

Big data-enabled transformation practices	Big data analytics capabilities				
	Traceability	Analytical	Decision support	Predictive	Total
Evidence-based medicine	1	27	16	2	46
Meaningful use of EHR	15	4	0	0	19
Multidisciplinary	0	1	6	0	7
Clinical resource integration	0	5	0	5	10
Network collaboration	0	4	0	2	6
Network knowledge creation	0	5	4	3	12
Personalized care	0	3	0	2	5
Total	16	49	26	14	105

Linking big data capabilities with potential benefits

Our results reveal that different big data capabilities and various combinations bring different benefits (see Tables 8). One particular big data capability, analytical capability, is associated with all five potential benefits with a total of 49 links which consist of IT infrastructure benefits (19 links), operational benefits (15 links), managerial benefits (7 links), organizational benefits (5 links), and strategic benefits (3 links). Decision support capability has the second highest count of links (26) but limited to only three benefits: organizational benefits (1 links), IT infrastructure benefits (6 links) and operational benefits (19 links). Traceability capability could potentially bring both IT infrastructure benefits (13 links) and operational benefits (3 links). Finally, predictive capability could potentially lead to IT infrastructure benefits (6 connections) and operational benefits (3 connections).

Overall, 80% of chains show that IT infrastructure and operational benefits can be acquired by the use of big data analytics. However, our results also demonstrate that big data analytics have a limited ability to help healthcare organizations gain organizational, strategic, or managerial benefits as of now.

Table 8. Number of pair-wise connections linking big data capabilities and potential benefits

Potential benefits of big data	Big data capabilities				
	Traceability	Analytical	Decision support	Predictive	Total
IT infrastructure benefits	13	19	6	6	44
Operational benefits	3	15	19	3	40
Organizational benefits	0	5	1	2	8
Managerial benefits	0	7	0	2	9
Strategic benefits	0	3	0	1	4
Total	16	49	26	14	105

Discussion of Path-to-value Chains

Three path-to-value chains were observed most frequently as shown in Appendix F. The first of these chains leads from analytical capability driven by data analysis components, through evidence-based medicine to IT infrastructure benefits (19 occurrences). The second, which starts with decision support capability trigged by data interpretation component and moves through evidence-based medicine practice to operational benefits, is equally significant (16 occurrences). The final chain, which goes from traceability enabled by data aggregation component, through meaningful use of EHR and IT infrastructure benefits, is slightly less common (13 occurrences). We did not present any process link from predictive capability because the frequency count is below the cut-off point (10 occurrences) we chose.

The first path-to-value chain

Evidence-based medicine practices are increasingly applied as an important way to ensure high quality care in healthcare settings (Straus et al., 2005). Big data analytics provide solutions to fill the growing need of healthcare managers to make better use of real-time data, unify all patients' medical records, and capture data from medical devices, thus supporting evidence-based medicine. It is now possible to identify new insights from massive healthcare record databases with ease as well as from large scale medical literature databases, which helps doctors and medical staffs make more accurate diagnoses and better treatment decisions. For example, Optum Labs have emphasized that analyzing findings from previous studies could be used to translate new evidences into routine clinical practices and thus drive healthcare transformation (Wallace et al., 2014)

In addition, analyzing a variety of patient data allows physicians to match treatments with evidence-supported outcomes that offer more reliable care to patients (Kudyba & Gregorio, 2010; Spruit et al., 2014). A recent study by Raghupathi and Raghupathi (2014) has reported that the Rizzoli Orthopedic Institute in Bologna, Italy, who analyzes patients' genomic data and case histories to determine hereditary diseases risks and to provide information of effective treatments for hereditary diseases. Their analytical capability is used to develop more evidence-based surgery protocols for patients with genetic disease, resulting in 60% reduction in imaging requests. Likewise, by using data mining approach, Dutch long-term care institution classifies all incidents into predefined categories and finds the causes of occurred incidents. Such analytical capability helps Dutch long-term care institution discover the facts to improve their patient safety (Spruit et al., 2014). We thus conclude that analytical capability can improve the quality of evidence-based medicine practices, which in turn facilitates IT infrastructure benefits.

The second path-to-value chain

Big data analytics has the potential to promote unity in evidence-based medical practices, particularly where decision support capability is implemented. The diverse outputs from big data analytics systems in the healthcare context, including clinical information displayed in visual metrics/dashboards, real-time monitoring of information (e.g., alerts and proactive notifications), real time data navigation, and operational key performance indicators (KPIs) accelerate healthcare organizations' ability to make sound decisions for daily clinical operations (Simpao et al., 2015a). These outputs as an important source of evidence are generally gathered from multiple sources such as clinical healthcare systems, smartphones and personal medical devices and sent on to relevant specialists in the teams or made available in the form of real time dashboards to monitor patients' health and prevent medical accidents. With these outputs to support decision support capability, our case hospitals (e.g., Mental Health Center of Denver and Kaiser Permanente Northern California) not only recognize feasible opportunities for quality improvement (Garrido et al., 2014; Samorani & LaGanga, 2015; McLaughlin et al., 2014), but also helps their analysts to recognize emerging healthcare issues such as medical errors, various patient safety issues and appropriate medication use (Simpao et al., 2015a; Simpao et al., 2015b). Thus, decision support capability can improve the quality of evidence-based medicine practices and consequently lead to operational benefits.

The third path-to-value chain

The use of EHR has the potential to enhance healthcare service efficiency and effectiveness, but this does not mean that simply adopting the system will produce those benefits. In the United States, the HITECH Act, which is part of the Recovery and Reinvestment Act of

2009, introduced a meaningful use guide for EHR, emphasizing that the main objective is to create digital medical records, including the entry of basic data, and optimize the utilization of EHR (Blumenthal & Tavenner 2010). To achieve meaningful use and avoid penalties, healthcare providers must follow a set of practices with core quality measures that serve as a guideline for effective using of EHR systems. This involves implementing two key practices: (1) facilitating basic EHR adoption and clinical data gathering; and (2) strengthening care coordination and exchange of patient information (Centers for Medicare & Medicaid Services, 2014).

From our results, big data analytics indeed has the potential to help healthcare organizations achieve the meaningful use of EHR practices. We found that adopting big data analytics in a healthcare organization makes it possible to maintain patient EHR data by tracking patients' demographics and health status, doctor prescriptions, and medications and diagnoses automatically (Bates et al., 2014; Halamka, 2014; Simpao et al., 2015a; Simpao et al., 2015b). Ideally, with traceability triggered by data aggregation tools such as data warehouse and ETL tools, healthcare organization can capture all patient data with ease from separate repositories ranging from single IT components, clinical offices (e.g., physicians, pharmacies, or research labs) to large state-level or national-level hospital networks. This permits data analysts to aggregate every patient's health records and transform them into meaningful information, and then present such information to eligible healthcare providers. By increasing data quality and coordination efficiency of EHRs, IT costs (e.g., reducing the load on working memory) and redundancies are reduced (Simpao et al., 2015a). One of our cases, Brigham and Women's Hospital (BWH) is a good example of high efficacy of in-depth traceability in longitudinal healthcare data. BWH integrates data mining algorithms with proper data rules into legacy IT systems to automatically monitor drug safety through tracking warning signals triggered by alarm systems. They use the traced data to implement drug-drug and drug-allergy interactions checks for EHR reporting and thus are able to identify drug-related risks at an earlier stage (Bates et al., 2014). Such traceability boosts EHR being used in a meaningful way, which in turn facilitates IT infrastructure benefits.

Contributions to Research

Big data-related technologies are probably the most influential innovations in the last decade. Resulted from such phenomenon, IS research has been focused on the technical side, not the managerial and/or strategic views, which further hinders the progress of IS business value research. One of the research gaps identified by Schryen (2013) after intensive literature review on IS business value is “IS business value creation process as grey box”, which indicates the need to research on “How, why and when do IS assets, IS capabilities and socio-organizational capabilities jointly create competitive value, thus performing a value creation process?” (p.159). One goal of this study is to explore the paths of the value creation process via IS. Intent to close such gap, we use the Bromiley and Rau (2014) PBV model as our base, we developed a generic Big data-enabled transformation (BDET) model for research/theory and then validated it empirically. Giving the lack of models to clarify the economic potential of big data technologies, our research's long term aim is to establish a framework for understanding how the IS architectural paradigm generates values. From our conceptual and exploratory work, we gained important insights into big data analytics and can be helpful to future IS research.

First, we presented a conceptual model, the big data enabled transformation model (BDET), which is among the first attempts to systematically capture the complex relations that link big data resources and its capabilities with practices and the associated business value.

As the Bromiley and Rau (2014) PBV model, BDET also consists of four elements: explanatory variables, practices, intermediate outcomes, and performance. As aforementioned we propose big data analytics capabilities as the explanatory variables, and use them to explain how these capabilities improve a series of organizational practices, thereby generating potential benefits and improving the firm's performance. The BDET model ties big data analytics resources and capabilities, IT-enabled transformation practices, benefit dimensions, and firm performance together in a systematic fashion.

In addition, we also attempt to answer another IS research call to have an IT artifact for our study, we use big data technology as our focal artifact to study its business value. From a theoretical standpoint, we integrated RBV with PBV and IT business value to establish a new model, the BDET model which conceptually demonstrates that big data analytics capabilities lead to business value through enhancing a series of healthcare practices. Our exploratory study reveals the essential elements, connections, and path-to-value chains for an understanding healthcare transformation through big data analytics. To the best of our knowledge, this is a first study that took such unique approach integrating the most prominent IS theories, applying the new perspectives to a current IT innovation to show the "causal chains" of IS business value theoretically and empirically.

We also frame our research in a specific industry for various reasons. The first and most obvious one is that different industries have different needs or goals of using big data technology solutions. It is best to test a generic model in a specific context. To further test and validate the applicability of our PBV-based model, we chose the healthcare industry because although most business processes, that is, practices, are carried out by similar procedures, which PBV aims to "examines publicly known, imitable activities, or practices amenable to transfer across firms."

(Bromiley & Rau 2014, p.1249). As PBV offers a new and different perspective on strategy scholarship complementing extant views (Bromiley & Rau 2014, p.1255), we set out to explore, expand and validate via this study, specifically, try to find the potential explanations for performance variation of each “technique”. Most prior works focused on a technological understanding of big data rather than identifying the business value of big data analytics in healthcare settings. There have not been sufficient evidence of big data analytics investment benefits (Murdoch & Detsky, 2013; Shah & Patak, 2014). Our findings from case descriptions provide some theoretical insights for strategy researchers and guidance for practitioners.

Managerial Implications and Recommendations

Another reason to frame our study in healthcare is to answer the call from healthcare professionals and managers. Healthcare professionals advocate the urgencies and advantages of adopting big data analytics (Groves et al., 2013; Murdoch & Detsky 2013; Schouten, 2013). They claim that the application of big data analytics to health care is “inevitable” (Murdoch & Detsky, 2013) but need help from IS researchers to guide them. Healthcare industry usually lags behind the curve of IT innovation adoption. Considering the needs for cost effectiveness and high service quality demands, healthcare organizations have started paying attention to the phenomenon of big data related technologies and how such innovations can help them optimize the quality of care and simultaneously enhance their economic potential (Agarwal et al. 2010; Bhattacherjee et al. 2007; Chen et al., 2012; Goh et al. 2011; Mantzana et al. 2007). How to leverage big data technology to improve quality and efficiency of health care delivery is currently one of the most discussed topics in the fields of information systems (IS) and healthcare informatics. To do so, healthcare organizations need help from IS researchers to provide guidance for making meaningful use of data, and validations for their business case (Raghupathi & Raghupathi, 2014; Schroeck et al. 2012). While PBV purposely define practice in an ambiguous manner to accommodate the idiosyncratic nature of such construct, this study provides a good starting point in identifying specific variables, links and paths to health care organization performance, sort of opening the "black box" of the connections between layers. The four main elements of our BDET model are extracted from real-world cases which merits easy-to-follow scenarios for health care practitioners. Concur with other strategic management and IS researchers (e.g., Peppard et al., 2014), our study also indicates that the application of IS strategy as a practice brings strategic value for health care organizations and ultimately resulted in better performance.

Consistent with other studies, we found that healthcare transformation through implementing big data technologies is still in an early stage. Healthcare managers need to formulate appropriate big data strategies that will enable their organizations to move forward to be more efficient and effective. We classified four big data capabilities and found three path-to-performance chains that healthcare organization managers can use as templates to build their organizational big data capability according to their immediate and future plans.

Recommendations

Realizing benefits is not enough, the more important question is how healthcare organizations can rake in the bang for their buck. Among the four big data analytics capabilities identified, analytical capability and decision support capability were the top two most frequently coded. Analytical capability offers the ability to analyze large amount of healthcare data, by which improves IT efficiency and control costs. The first path-to-value chain leads from analytical capability, through evidence-based medicine to IT infrastructure benefits.

Decision support is another crucial capability of big data analytics systems due to its ability to create meaningful reports. The second chain starts with decision support capability and moves through evidence-based medicine to operational benefits. The key to use reports effectively is to equip managers and employees with relevant professional competencies, such as the skills of making an appropriate interpretation of the results and critical thinking. According to American Management Association (2013) 64% of organizations in the United States fail to meet all of their expected analyzing data skills needed in the workplace. In this regard, incorrect interpretation of the reports generated could lead to serious errors of judgment and questionable decisions.

To fully take advantage of these findings, it is important that healthcare organizations provide analytical training courses in areas such as basic statistics, data mining and business intelligence to those employees who will play a critical support role in the new information-rich work environment. Mentoring, cross-functional team-based training and self-study are also beneficial training approaches to help employees develop the big data analytical skills they will need. Alternatively, healthcare organizations can adjust their job selection criteria to recruit prospective employees who already have the necessary analytical skills.

The third path-to-value chain which goes from traceability through meaningful use of EHR to IT infrastructure benefits is slightly less common than the first two chains. To comply with the Patient Protection and Affordable Care Act (PPACA) of 2010, healthcare organizations need to keep detailed and updated data. Traceability is the ability to track output data from all the system’s IT components throughout the organization’s service units and thus could help in keeping real-time updates. Our results show that this capability is still underutilized maybe because healthcare managers have not recognize the potential benefits or are cost sensitive.

The fourth capability identified was the predictive capability. Although the frequency count of the path-to-performance chain this capability leads was below our cut-off criteria, it still provides some practical value because it can help to generate new ideas. New idea generation is not only necessary for organizational innovation, but also can lead to changes in business operations that will increase productivity and build competitive advantages. This could be achieved through the use of powerful big data predictive analytics tools. These tools can provide detailed reporting and identify market trends that allow companies to accelerate new business ideas and generate creative thinking. In addition to using big data to answer known questions, managers should encourage users to leverage big data outputs to discover new ideas and market opportunities, and assess the feasibility of ideas.

To follow the path-to-value chains and to enjoy all the benefits, merely implementation of big data technologies is not enough. A crucial component for success is the management of technology, specifically the governance of the IT infrastructure. Big data governance is an extension of IT governance that focuses on leveraging enterprise-wide big data resources to create business value. Big data is a double-edged sword for IT investment, potentially incurring huge financial costs for healthcare organizations due to poor governance. On the other hand, with appropriate data governance, big data has the potential to equip organizations with the tools they need to harness the mountains of heterogeneous data, information, and knowledge that they routinely gather, disentangle intricate customer networks and develop a new portfolio of business strategies for products and services.

Successful big data governance requires a series of organizational changes in business processes. Several issues should be taken into consideration when developing big data governance for a healthcare organization. The first step is to formulate the governance mission, with clearly focused goals, execution procedures, governance metrics, and performance measures. In other words, a strong data governance protocol should be defined that provides clear guidelines for data availability, criticality, authenticity, sharing, and retention that enable companies to harness data effectively from the time it is acquired, stored, analyzed, and finally used. This allows healthcare organizations to ensure the appropriate use of big data analytics and build sustainable competitive advantages. Second, healthcare organizations should review the data they gather within all their units and realize their value. Once the value of these data has been defined, managers can make decisions on which datasets to be incorporated in their big data framework, thereby minimizing cost and complexity. Finally, information integration is the key to success in big data implementation, because the challenges involved in integrating information across systems and data sources within the enterprise remain problematic in many instances. In particular, most healthcare organizations encounter difficulties in integrating the data from legacy systems into big data frameworks. Managers need to develop robust data governance before introducing big data in their organization.

Limitations

Notwithstanding the above-mentioned contributions and implications, our study is subject to limitations. One challenge in the health care industry is that their IT adoption usually lags behind other industries. Case organizations studied in this paper are "leaders" in their own rights. They are either top-ranked research hospitals or associated with top medical schools with resources, or highly profitable entities. We have not found “small” healthcare organizations that could afford big data technologies to enjoy the benefits we presented by our findings.

In addition, the performance measures used by both academia and industries are financially related, based on easy to measure outputs such as profitability and return of investment. Due to the unique aspects of the healthcare field, scholars have posited that the metrics used for healthcare organization performance should be different from those used for commercial organizations.

Future Research

Our exploratory study reveals the essential elements, links, and path-to-value chains for an understanding of big data enabled transformation. One limitation of this study is the data source. Further and better validation of the BDET model could be done through collecting and analyzing primary data. Given the growing number of healthcare organizations adopting big data technologies, the sample frame for collecting primary data is larger. Examining BDET model and our findings with quantitative analysis method based on primary data could shed different lights. With quantitative method, correlations, effect sizes and relationships are quantified. However, to carry out a quantitative study, a valid scale for big data analytics capabilities is needed.

In addition to requiring empirical analysis of big data enabled transformation, our study also exposes the needs for more scientific and quantitative studies, focusing on some of the big data capability elements we identified. This especially applies to the two most frequently cited big data capabilities, analytical capability and decision support capability in our cases, With a growing amount of diverse and unstructured data, there is an urgent need for advanced analytic techniques, such as deep machine learning algorithms that instruct computers to detect items of interest in large quantities of unstructured and binary data, and to deduce relationships without needing specific models or programming instructions (Computerworld, 2014). We thus expect future scientific studies that develop efficient unstructured data analytical algorithms and applications as primary technological developments.

Future research may also consider using in-depth single or multiple cases studies to explain how and why big data capabilities help improve specific IT-enabled transformation practices. This particularly applies to the most frequent path-to-value chain, which leads from analytical capability, through evidence-based medicine and IT infrastructure benefits to profitability. Such case studies allow academics and practitioners to a more granular understanding of big data management best practices in real-world.

Different industries have different needs or goals of using big data technology solutions. We targeted healthcare for this study. Hence, the results are industry-specific. Future research can apply the BDET model to other industries. Different big data capabilities, practices, benefits and outcomes might surface.

In light of these future opportunities, we believe the big data research stream with a focus on strategic view has great potential to help balance the number of studies of big data from technological and managerial-oriented perspectives.

Appendix A: Prior Literature Related to the Business Value of Big data Analytics

Theories for assessing big data analytics' business value	Authors	Research methods	Key findings
Information processing view	Cao et al. (2015)	Survey	• Develop a model linking the use of business analytics tools to organizational decision-making effectiveness • Business analytics are shown to indirectly influence information processing capability through a mediating role of data-driven environment which in turn has a positive effect on decision-making effectiveness.
	Trkman et al. (2010)	Survey	• Conceptualize the use of big data analytics in different supply chain areas based on supply chain operations reference (SCOR) model • Suggest that analytics capabilities in terms of plan, source, make, and delivery can positively influence supply chain performance.
	Kowalczyk & Buxmann (2014)	Multiple case studies	• Investigate how different type of big data and information processing mechanism contributes to decision process
Resource based view (RBV)	Wixom et al. (2013)	Single case study	• Explore two key factors (i.e., speed to insight and pervasive use) and their underlying dimensions for maximizing the business value of big data analytics in a fashion retailer case • Provide actionable practices (e.g., agile methods, co-location, and templates) driving the business value of big data analytics
	Kwon et al. (2014)	Survey	• Data quality management and data usage capabilities could have significant effects on the adoption intention of big data analytics • utilizing external source data could encourage future acquisition of big data analytics
	Işık et al.(2013)	Survey	• Technological capabilities such as data quality, user access and the integration of business intelligence with other systems as well as business intelligence (BI) flexibility are necessary for BI success.
	Tamm et al. (2013)	Interviews	• Elaborate how analytics users (i.e., analytics professionals and analytics end-users) lead to three pathways to value from big data analytics
	Seddon et al. (2012)	Multiple case studies	• Develop long-term and short-term business analytics models to identify critical factors leading to organizational benefits • Functional fit of big data tools, readily available high-quality data, analytical people, overcoming organizational inertia have been recognized to drive big data implementation

Integrating RBV with dynamic capabilities view	Shanks & Bekmanedova (2012)	Single case study	• Explain how business analytics systems can create values by orchestrating business analytics-enabled organizational capabilities and dynamic capabilities over time
	Knabke & Olbrich (2015)	Conceptual	• Investigate how current business trends affect data warehouse-based business intelligence (BI) and dynamic BI capabilities, and in turn lead to support decision making
	Chasalow & Baker (2015)	Survey	• Dynamic capabilities driven by business intelligence were not affected by organizational process, firm IT assets, and firm history.
	Erevelles et al. (2016)	Conceptual	• A firm's resource helps transform data into valuable consumers' insights that accelerate dynamic and adaptive capabilities • Adaptive and dynamic capabilities, triggered by consumers' insights from big data analytics, lead to value creation regarding marketing activities

Appendix B. A List of Big Data Cases

No.	Case Name	Country	Sources
1	Children's Hospital of Philadelphia	United States	Gálvez et al. (2014); Simpao et al. (2015a); Simpao et al. (2015b)
2	Brigham and Women's hospital	United States	Bates et al. (2014)
3	Mental Health Center of Denver	United States	Samorani & LaGanga (2015)
4	North Texas Hospitals System	United States	Bardhan et al. (2015)
5	Beth Israel Deaconess Medical Center	United States	Halamka (2014)
6	Private Health Insurer	Australia	Srinivasan & Arunasalam (2013); Srinivasan 2014
7	Neonatal intensive care units in The Hospital for Sick Children	Canada	Blount et al. (2010)
8	Chicago Department of Public Health	United States	Choucair et al. (2015)
9	Case Western University Hospital	United States	Sahoo et al. (2014)
10	Centers for Medicare and Medicaid Services (CMS)	United States	Brennan et al. (2014)
11	Cardinal Health	United States	Carte et al. (2005)
12	University of Utah Health Sciences Center	United States	Kawamoto et al. (2014)
13	United Health Services Hospitals	United States	Agnihothri et al. (2015)
14	OCHIN Community Health Information Network	United States	DeVoe et al. (2014)
15	Dutch long-term care institution	Netherlands	Spruit et al. (2014)
16	Guysborough Antigonish Strait Health Authority	Canada	Foshay & Kuziemsky (2014)
17	UCLA Medical Center	United States	McLaughlin et al. (2014)
18	Department of Health Western Australia	Australia	Jardine et al. (2014)
19	Optum Labs	United States	Wallace et al. (2014)
20	Children's Healthcare of Atlanta	United States	Basole et al. (2015)
21	Duke University Health System	United States	Ferranti et al. (2010)
22	Newark Beth Israel Medical Center	United States	Kudyba & Gregorio (2010)
23	Jinhua Municipal Central Hospital	China	Zhang (2014a); Zhang (2014b)
24	Cardiac surgery Centre in New Delhi	India	Jhajharia et al. (2015)
25	Veterans Health Administration	United States	Ghosh & Scott (2011); Fihn et al. (2014)
26	Kaiser Permanente Northern California	United States	Garrido et al. (2014); Bates et al. (2014)
27	NorthShore University Health System	United States	Degaspari (2013)
28	MedStar Health	United States	Ratwani & Fong (2014)

References

Agnihothri, S., Banerjee, A., & Thalacker, G. (2015). Analytics to Improve Service in a Pre-admission Testing Clinic. In System Sciences (HICSS), 2015 48th Hawaii International Conference on (pp. 1325-1331). IEEE.

Bardhan, I., Oh, J. H., Zheng, Z., & Kirksey, K. (2015). Predictive Analytics for Readmission of Patients with Congestive Heart Failure. *Information Systems Research*, 26(1), 19-39.

Basole, R. C., Braunstein, M. L., Kumar, V., Park, H., Kahng, M., Chau, D. H. P., ... & Lesnick, B. (2015). Understanding variations in pediatric asthma care processes in the emergency department using visual analytics. *Journal of the American Medical Informatics Association*, 22(2), 318-323.

Bates, D. W., Saria, S., Ohno-Machado, L., Shah, A., & Escobar, G. (2014). Big data in health care: using analytics to identify and manage high-risk and high-cost patients. *Health Affairs*, 33(7), 1123-1131.

Blount, M., Ebling, M. R., Eklund, J. M., James, A. G., McGregor, C., Percival, N., ... & Sow, D. (2010). Real-time analysis for intensive care: development and deployment of the artemis analytic system. *Engineering in Medicine and Biology Magazine, IEEE*, 29(2), 110-118.

Brennan, N., Oelschlaeger, A., Cox, C., & Tavenner, M. (2014). Leveraging the big-data revolution: CMS is expanding capabilities to spur health system transformation. *Health Affairs*, 33(7), 1195-1202.

Carte, T., Schwarzkopf, A. B., Shaft, T. M., & Zund, R. W. (2005). Advanced business intelligence at Cardinal Health. *MIS Quarterly Executive*, 4(4), 413-424.

Choucair, B., Bhatt, J., & Mansour, R. (2015). A bright future: innovation transforming public health in Chicago. *Journal of Public Health Management and Practice*, 21(1), S49-S55.

Degaspari, J. (2013). NorthShore University Health System. Electronic surveillance system flags undiagnosed hypertensive patients. *Healthcare informatics: the business magazine for information and communication systems*, 30(1), 12-14.

DeVoe, J. E., Gold, R., Cottrell, E., Bauer, V., Brickman, A., Puro, J., ... & Merrell, J. (2014). The ADVANCE network: accelerating data value across a national community health center network. *Journal of the American Medical Informatics Association*, 21(4), 591-595.

Ferranti, J. M., Langman, M. K., Tanaka, D., McCall, J., & Ahmad, A. (2010). Bridging the gap: leveraging business intelligence tools in support of patient safety and financial effectiveness. *Journal of the American Medical Informatics Association*, 17(2), 136-143.

Fihn, S. D., Francis, J., Clancy, C., Nielson, C., Nelson, K., Rumsfeld, J., ... & Graham, G. L. (2014). Insights from advanced analytics at the Veterans Health Administration. *Health Affairs*, 33(7), 1203-1211.

Foshay, N., & Kuziemsky, C. (2014). Towards an implementation framework for business intelligence in healthcare. *International Journal of Information Management*, 34(1), 20-27.

Gálvez, J. A., Ahumada, L., Simpao, A. F., Lin, E. E., Bonafide, C. P., Choudhry, D., ... & Rehman, M. A. (2014). Visual analytical tool for evaluation of 10-year perioperative transfusion practice at a children's hospital. *Journal of the American Medical Informatics Association*, 21(3), 529-534.

Garrido, T., Kumar, S., Lekas, J., Lindberg, M., Kadiyala, D., Whippy, A., ... & Weissberg, J. (2014). e-Measures: insight into the challenges and opportunities of automating publicly reported quality measures. *Journal of the American Medical Informatics Association*, 21(1), 181-184.

Ghosh, B., & Scott, J. E. (2011). Antecedents and catalysts for developing a healthcare analytic capability. *Communications of the Association for Information Systems*, 29(1), 395-409.

Halamka, J. D. (2014). Early experiences with big data at an academic medical center. *Health Affairs*, 33(7), 1132-1138.

Jardine, A., Mullan, N., Gudes, O., Cosford, J., Moncrieff, S., West, G., ... & Someford, P. (2014). Web-based geo-visualisation of spatial information to support evidence-based health policy: A case study of the development process of 'Health Tracks'. *Health Information Management Journal*, 43(2), 7-16.

Jhajharia, S., Pal, S.K.,Verma, S., & Kumar, M. (2015). Predictive Analytics for Better Health and Disease Reduction. 1st IIMA International Conference on Advances in Healthcare Management Services. Indian Institute of Management, Ahmedabad.

Kawamoto, K., Martin, C. J., Williams, K., Tu, M. C., Park, C. G., Hunter, C., ... & Morris, S. J. (2014). Value Driven Outcomes (VDO): a pragmatic, modular, and extensible software framework for understanding and improving health care costs and outcomes. *Journal of the American Medical Informatics Association*, 22(1), 223-235.

Kudyba, S., & Gregorio, T. (2010). Identifying factors that impact patient length of stay metrics for healthcare providers with advanced analytics. *Health Informatics Journal*, 16(4), 235-245.

McLaughlin, N., Afsar-manesh, N., Ragland, V., Buxey, F., & Martin, N. A. (2014). Tracking and sustaining improvement initiatives: leveraging quality dashboards to lead change in a neurosurgical department. *Neurosurgery*, 74(3), 235-244.

Ratwani, R. M., & Fong, A. (2014). “Connecting the dots”: leveraging visual analytics to make sense of patient safety event reports. *Journal of the American Medical Informatics Association*, 22(2), 312-317.

Sahoo, S. S., Jayapandian, C., Garg, G., Kaffashi, F., Chung, S., Bozorgi, A., ... & Zhang, G. Q. (2014). Heart beats in the cloud: distributed analysis of electrophysiological ‘Big Data’ using cloud computing for epilepsy clinical research. *Journal of the American Medical Informatics Association*, 21(2), 263-271.

Samorani, M., & LaGanga, L. R. (2015). Outpatient appointment scheduling given individual day-dependent no-show predictions. *European Journal of Operational Research*, 240(1), 245-257.

Simpao, A. F., Ahumada, L. M., & Rehman, M. A. (2015a). Big data and visual analytics in anaesthesia and health care. *British Journal of Anaesthesia*, 115(3):350-356.

Simpao, A. F., Ahumada, L. M., Desai, B. R., Bonafide, C. P., Gálvez, J. A., Rehman, M. A., ... & Shelov, E. D. (2015b). Optimization of drug–drug interaction alert rules in a pediatric hospital's electronic health record system using a visual analytics dashboard. *Journal of the American Medical Informatics Association*, 22, 361-369.

Spruit, M., Vroon, R., & Batenburg, R. (2014). Towards healthcare business intelligence in long-term care: An explorative case study in the Netherlands. *Computers in Human Behavior*, 30, 698-707.

Srinivasan, U. (2014). Anomalies Detection in Healthcare Services. *IT Professional*, 6, 12-15.

Srinivasan, U., & Arunasalam, B. (2013). Leveraging big data analytics to reduce healthcare costs. *IT Professional*, 15(6), 21-28.

Wallace, P. J., Shah, N. D., Dennen, T., Bleicher, P. A., & Crown, W. H. (2014). Optum Labs: building a novel node in the learning health care system. *Health Affairs*, 33(7), 1187-1194.

Zhang, Z. (2014a). Big data and clinical research: focusing on the area of critical care medicine in mainland China. *Quantitative Imaging in Medicine and Surgery*, 4(5), 426-429.

Zhang, Z. (2014b). Big data and clinical research: perspective from a clinician. *Journal of Thoracic Disease*, 6(12), 1659-1664.

Appendix C. Defining the Initial Elements of Connecting Layers

Elements	Descriptions	Sources
Traceability	Integrate and track the patient data from all of the IT components throughout the various healthcare service units	Wang et al. (2015)
Analytical capability	Enable users to process clinical data with an immense volume (from terabytes to exabytes), variety (from text to graph) and velocity (from batch to streaming) by using descriptive analytics techniques	Watson (2014); Seddon et al. (2012); Cao et al. (2015)
Decision support capability	Produce outputs regarding patients, care process and service to guide diagnostic and treatment decisions	Groves et al. (2013)
Predictive capability	Explore data and identify useful correlations, patterns and trends and extrapolate them to forecast what is likely to occur in the future	Negash (2004); Hurwitz et al. (2013)
Evidence-based medicine	Integrate individual clinical expertise with the best available external clinical evidence from systematic research	Sackett et al. (1996); Straus et al. (2005)
Meaningful use of EHR	The practices that realize the true potential of EHR to improve the safety, quality, and efficiency of care	Blumenthal & Tavenner (2010); DesRoches et al. (2013)
Multidisciplinary	Practices draw from multiple specialties with coordinated, interrelated behaviors	Oborn and Dawson (2010); Oborn et al. (2011)
Clinical resource integration	The practices which patient care services are coordinated across the various functions, activities, and operating units of a system	Miller (1996)
Network collaboration	The practices which concentrate on the collaboration between care providers and other stakeholders in terms of dedicated care management resources, data reporting, and quality measurement	Claffey et al. (2012)
Network knowledge creation	The practices which incorporate new explicit and tacit knowledge generated from healthcare networks into the clinical routines	Abidi et al. (2005); Nicolini et al. (2008)
Personalized care	The practices which seek to identify the optimal treatment for each individual patient to stratify patients for specific therapies and minimize adverse effects by utilizing clinical information.	Ogino et al. (2011); Schleidgen et al. (2013)

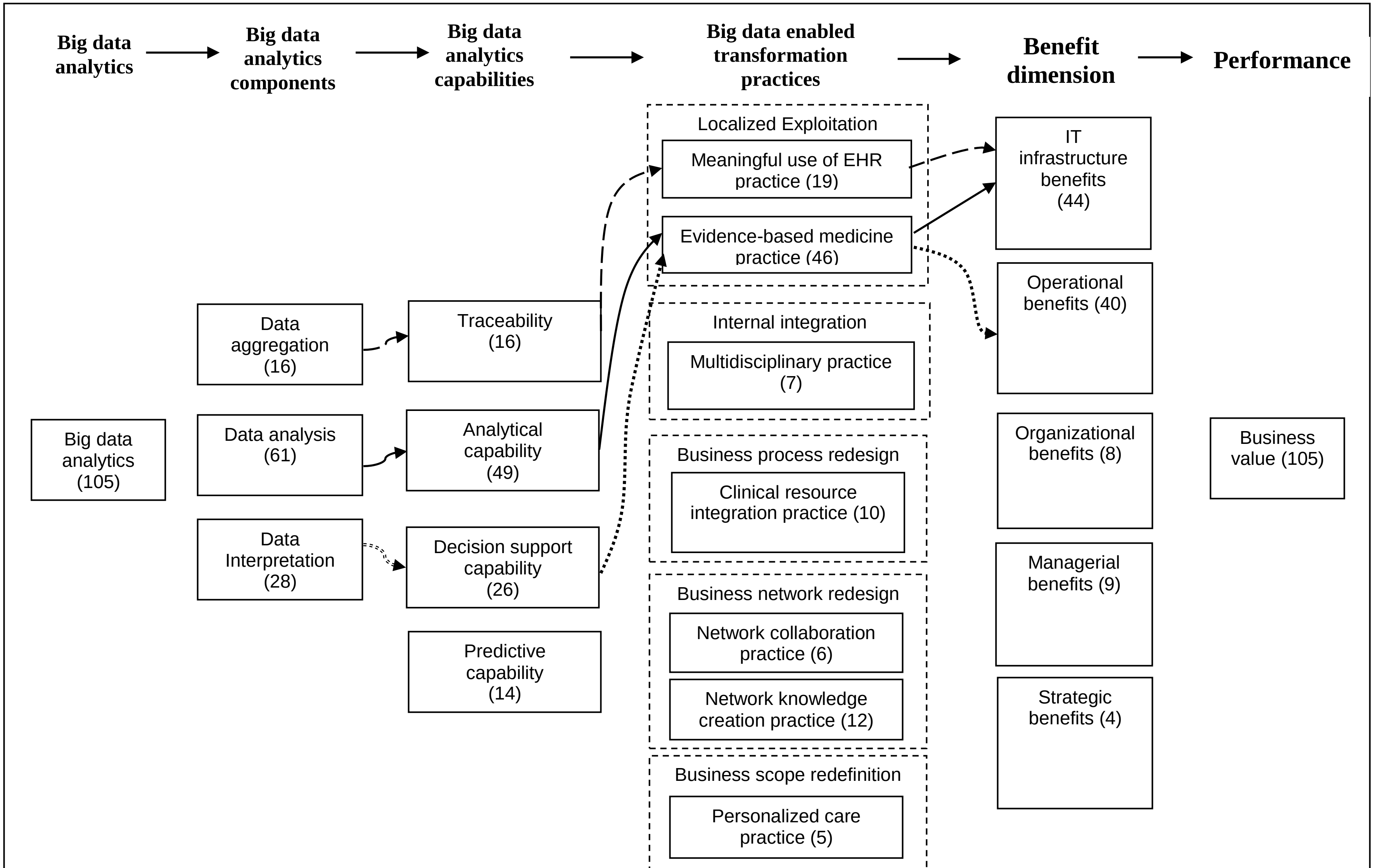
Appendix D. Coding Example A

Statements	Open (<u>underlined</u>) and axial (*italic*) Coding	Path-to-value chains confirmed by selective coding
Children's Hospital of Philadelphia (Case #1) "Several steps are required to visualize big data using visual analytics tools. First, the data are stored in a dimensional database model….Dimensional models create a unique fact table that contains all potential data transactions in addition to filters used to associate facts and measures throughout the database. Our hospital uses VA to monitor hand hygiene compliance, nursing metrics, supply chain performance, and adherence to clinical guidelines (e.g. Febrile Infant Pathway dashboard). Many additional examples of VA applications in health care are available, such as for visualizing dynamic data from multiple EHRs, tracking symptom evolution during disease progression……….. This enables the user to explore alert from electronic health record medication data and historic blood transfusion data (based on patient characteristics and procedure type)…....this tool offers benefits compared with traditional database queries: the user can explore big data in a self-service point-and-click fashion as opposed to writing database queries manually. Complex ideas can be communicated with clarity and efficiency in visual graphs rather than the tabular data output from a traditional database query." (Simpao et al., 2015a)	<u>Data aggregation component</u> *Data storage by dimensional models* <u>Traceability</u> *Track medical events based on the rules that built on hospital claims* <u>Meaningful use of EHR</u> *Generate lists of patients by specific conditions to use for quality improvement* <u>IT infrastructure benefit</u> *Gain better IT effectiveness compared to the traditional database environments*	• Comparing this statement to other similarly coded elements (i.e., data aggregation component, traceability, and meaningful use of EHR, and IT infrastructure benefit. • Both coders from expert panel agreed on traceability, driven by data aggregation can lead to improve meaningful used of EHR practice, thereby facilitating IT infrastructure benefit • Recording this statement as one of the path-to-value chain: Data aggregation →Traceability→ Meaningful use of EHR practice →IT infrastructure benefit

Appendix E. Coding Example B

Statements	Open (<u>underlined</u>) and axial (*italic*) Coding	Path-to-value chains confirmed by selective coding
Dutch long-term care institution (Case #15) "The dataset contains 6126 incidents, which includes attributes such as client, department, date and time, type of incident, cause, location, physical damage and mental damage. This collection of data is very valuable, and could be used for various analyses. First of all, all incidents are selected for which a client, department, date and time, type of incident and location are registered, which results in a collection of 5692 incidents. ……Fig. 1 shows an upward trend, this does not necessarily indicate that increasingly more incidents have happened. We assume that a better registration of incidents is most likely the cause of this trend. For this analysis, all incidents were grouped per hour using a SQL query which counts the number of incidents between, for example, 00:00 and 00:59. Fig. 2 visualizes the number of incidents at a certain time of day. It turns out that most incidents occur during the day, between 08:00 and 09:00. The peaks between 08:00 and 09:00 and between 17:00 and 18:00 are most likely caused by the transfers of the clients (e.g. getting out of bed and going towards diner). Also, the location of the incidents is being registered, which could be used to detect geographical problem areas at the care institution. These results could trigger management to research this fact and to increase safety in the corridor……….. For all care institution locations it becomes clear that most incidents take place in the living room. The other locations where incidents commonly occur are the bedroom, kitchen and bathroom. For these (problem) areas the percentages are described per location, which makes it possible to compare the locations with each other" (Spruit et al., 2014)	<u>Data aggregation component</u> *Collect data from multiple sources and integrate into* <u>Analytical capability</u> *Explore the causes of occurred medical events from relational databases* <u>Evidence-based medicine</u> *Explore the fact from medical events to improve a specific outcome* <u>Operational benefit</u> *Understand on incident locations and causes to improve workflow efficiency*	• Comparing this statement to other similarly coded elements (i.e., data aggregation component, analytical capability, and evidence-based medicine practice, and operational benefit. • A discrepancy on analytical capability occurred between the two coders. The first coder agreed that the analysis provides the trends and patterns to predict incidents and coded it as predictive capability in the first place. However, the second coder argued that the analysis only presents the summarized results according the current 5,692 incidents and there is not enough information about the predictions of future incident trend. • After discussion and debate, both coders agreed that ECR software allows users to collect data from multiple sources that facilitate data analysis capabilities. Such capabilities enable managers to make decisions based on the evidences, thus resulting in obtaining operational benefits. • Recording this statement as one of the path-to-value chain: Data aggregation→Analytical capability→Evidence-based medicine practice →Operational benefit

Appendix F. The Results of the Big Data Analytics-Enabled Transformation Model



Note: (#) represents number of times this element was coded in the cases analyzed.

→ represents the highest path-to-value chains (19); – –→ represents the second highest path-to-value chains (16)

·······→ represents the third highest path-to-value chains (13)

References

Abidi, S. S. R., Cheah, Y. N., & Curran, J. (2005). A knowledge creation info-structure to acquire and crystallize the tacit knowledge of health-care experts. *Information Technology in Biomedicine, IEEE Transactions on*, 9(2), 193-204.

Agarwal, R., Gao, G., DesRoches, C., & Jha, A.K. (2010). The digital transformation of healthcare: current status and the road ahead. *Information Systems Research*, 21(4), 796-809.

Amarasingham, R., Patzer, R. E., Huesch, M., Nguyen, N. Q., & Xie, B. (2014). Implementing electronic health care predictive analytics: considerations and challenges. *Health Affairs*, 33(7), 1148-1154.

American Management Association (AMA). (2013). Conquering Big Data: Building Analytical Skills in Your Organization, American Management Association Press.

Angus, D. C. (2015). Fusing randomized trials with big data: The key to self-learning health care systems? *Journal of American Medical Association*, *314*(8), 767-768.

Arvidsson, V., Holmström, J., & Lyytinen, K. (2014). Information systems use as strategy practice: A multi-dimensional view of strategic information system implementation and use. *The Journal of Strategic Information Systems*, 23(1), 45-61.

Ashrafi, N., Kelleher, L., & Kuilboer, J. P. (2014). The impact of business intelligence on healthcare delivery in the USA. *Interdisciplinary Journal of Information, Knowledge, and Management*, 9, 117-130.

Azad, B., & King, N. (2008). Enacting computer workaroud practices within a medication dispensing system. *European Journal of Information Systems*, 17(3), 264-278.

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, 17(1), 99-120.

Barney, J. B. (2001). Resource-based theories of competitive advantage: A ten-year retrospective on the resource-based view. *Journal of Management*, 27(6), 643-650.

Bates, D. W., Kuperman, G. J., Wang, S., Gandhi, T., Kittler, A., Volk, L., ... & Middleton, B. (2003). Ten commandments for effective clinical decision support: making the practice of evidence-based medicine a reality. *Journal of the American Medical Informatics Association*, 10(6), 523-530.

Bates, D.W., Saria, S., Ohno-Machado, L., Shah, A., & Escobar, G. (2014). Big Data in Health Care: Using Analytics to Identify and Manage High-Risk and High-Cost Patients. Health Affairs, 33(7), 1123-1131.

Belle, A., Thiagarajan, R., Soroushmehr, S. M., Navidi, F., Beard, D. A., & Najarian, K. (2015). Big Data Analytics in Healthcare. *BioMed Research International*, 1-16.

Bharadwaj, A. S. (2000). A resource-based perspective on information Technology capability and firm performance: An empirical investigation. *MIS Quarterly*, 24(1), 169-196.

Bhattacherjee, A., Hikmet, N., Menachemi, N., Kayhan, V. O., & Brooks, R. G. (2006). The differential performance effects of healthcare information technology adoption. *Information Systems Management*, 24(1), 5-14.

Bjørn, P., Burgoyne, S., Crompton, V., Macdonald, T., Pickering, B., & Munro, S. (2009). Boundary factors and contextual contingencies: Configuring electronic templates for healthcare professionals. *European Journal of Information Syste*ms, 18(5), 428-441.

Bloom, N., Eifert, B., Mahajan, A., McKenzie, D., & Roberts, J. (2013). Does management matter? Evidence from India. *Quarterly Journal of Economics*, 128(1), 1-51.

Blumenthal, D., & Tavenner, M. (2010). The “meaningful use” regulation for electronic health records. *New England Journal of Medicine*, 363(6), 501-504.

Boulus, N., & Bjørn, P. (2008). A cross-case analysis of technology-in-use practices: EPR-adaptation in Canada and Norway. *International Journal of Medical Informatics*, 79(6), e97-e108.

Bromiley, P., & Rau, D. (2014). Towards a practice-based view of strategy. *Strategic Management Journal*, 35, 1249-1256.

Brooks, P., El-Gayar, O., & Sarnikar, S. (2015). A framework for developing a domain specific business intelligence maturity model: Application to healthcare. *International Journal of Information Management*, 35(3), 337-345.

Cao, G., Duan, Y., & Li, G. (2015). Linking business analytics to decision making effectiveness: A path model analysis. *IEEE Transactions on Engineering Management*, 62(3), 384 - 395

Centers for Medicare & Medicaid Services. (2014). An Introduction to Stage 1 of the Medicaid EHR Incentive Program for Eligible Professionals, Centers for Medicare and Medicaid Services.

Cha, S., Abusharekh, A., & Abidi Sr, S. (2015). Towards a'Big'Health Data Analytics Platform. In Big Data Computing Service and Applications (BigDataService), 2015 IEEE First International Conference on (pp. 233-241). IEEE.

Chae, B., Olson, D., & Sheu, C. (2014). The impact of supply chain analytics on operational performance: a resource-based view. *International Journal of Production Research*, 52(16), 4695-4710.

Chan, J. O. (2014). An architecture for big data analytics. *Communications of the IIMA*, 13(2), 1.

Chasalow, L. C., & Baker, E. W. (2015). Factors contributing to business intelligence success: The impact of dynamic capabilities. In Proceeding of Twenty-first Americas Conference on Information Systems, Puerto Rico, USA.

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

Claffey, T. F., Agostini, J. V., Collet, E. N., Reisman, L., & Krakauer, R. (2012). Payer-provider collaboration in accountable care reduced use and improved quality in Maine medicare advantage plan. *Health Affairs*, 31(9), 2074-2083.

Computerworld. (2014). 8 Big Trends in Big Data Analytics. Computerworld.com.

Cortada, J.W. Gordon, D., & Lenihan, B. (2012). *The Value of Analytics in Healthcare: From Insights to Outcomes*. Somers, NY: IBM Global Business Services.

Davenport, T. H., & Harris, J. G. (2007). Competing on analytics: The new science of winning. Harvard Business Press.

Dehning, B., Richardson, V., & Zmud, R. (2003). The value relevance of announcements of transformational information technology investments. *MIS Quarterly*, 27(4), 637-656.

Delen, D. (2014). *Real-World Data Mining: Applied Business Analytics and Decision Making*. FT Press.

DesRoches, C. M., Audet, A. M., Painter, M., & Donelan, K. (2013). Meeting meaningful use criteria and managing patient populations: a national survey of practicing physicians. *Annals of Internal Medicine*, 158(11), 791-799.

Devaraj, S., & Kohli, R. (2003). Performance impacts of information technology: Is actual usage the missing link?. *Management Science*, 49(3), 273-289.

Doherty, N. F., & Terry, M. (2009). The role of IS capability in delivering sustainable improvements to competitive positioning. *Journal of Strategic Information Systems*, 18(2), 100-116.

Eisenhardt, K. M., & Graebner, M. E. (2007). Theory building from cases: opportunities and challenges. *Academy of Management Journal*, 50(1), 25-32.

Eisenhardt, K.M. (1998). Building theories from case study research. *Academy of Management Journal*, 14, 532-550.

El Sawy, O. A. Malhotra, A. Park, Y., & Pavlou, P. A. (2010), Seeking the configurations of digital ecodynamics: It takes three to tango. *Information Systems Research*, 21(4), 835-848.

Elo, S. & Kyngäs, H. (2008). The qualitative content analysis process. *Journal of Advanced Nursing*, 62(1), 107-115.

Erevelles, S., Fukawa, N., & Swayne, L. (2016). Big data consumer analytics and the transformation of marketing. *Journal of Business Research*, 69(2), 897-904.

Esteves, J. (2009). A benefits realisation road-map framework for ERP usage in small and medium-sized enterprises. *Journal of Enterprise Information Management*, 22(1/2), 25-35.

Garrido, T., Kumar, S., Lekas, J., Lindberg, M., Kadiyala, D., Whippy, A., ... & Weissberg, J. (2014). e-Measures: insight into the challenges and opportunities of automating publicly reported quality measures. *Journal of the American Medical Informatics Association*, 21(1), 181-184.

Gastaldi, L., Pietrosi, A., & Corso, M. (2014). Measuring the maturity of business intelligence in healthcare: Supporting the development of a roadmap towards precision medicine. In *Proceeding of the 15th International Continuous Innovation Network (CINet) Conference*. Budapest, Hungary

Gefen, D., & Ragowsky, A. (2005). A multi-level approach to measuring the benefits of an ERP system in manufacturing firms. *Information Systems Management*, 22(1), 18-25.

Ghosh, B., & Scott, J. E. (2011). Antecedents and catalysts for developing a healthcare analytic capability. *Communications of the Association for Information Systems*, 29(1), 395-409.

Giannopoulou, E., Gryszkiewicz, L., & Barlatier, P. J. 2014. Creativity for service innovation: A practice-based perspective. *Managing Service Quality*, 24(1), 23-44.

Gillon, K., Aral, S., Lin, C. Y., Mithas, S., & Zozulia, M. (2014). Business analytics: radical shift or incremental change? *Communications of the Association for Information Systems*, 34, 287-296.

Goh, J. M., Gao, G., & Agarwal, R. (2011). Evolving work routines: adaptive routinization of information technology in healthcare. *Information Systems Research*, 22(3), 565-585.

Gregor, S. (2006). The nature of theory in information systems. *MIS Quarterly*, 30(3), 611-642.

Groves, P., Kayyali, B., Knott, D., & Kuiken, S. V. 2013. *The "Big Data" Revolution in Healthcare: Accelerating Value and Innovation*. McKinsey & Company.

Halamka, J.D. (2014). Early experiences with big data at an Academic Medical Center. *Health Affairs*, 33(7), 1132-1138.

Hamilton, B. (2012). *Big Data is the Future of Healthcare*. NJ: Cognizant.

Hsieh, H.F., & Shannon, S.E. (2005). Three approaches to qualitative content analysis. *Qualitative Health Research*, 15(9), 1277-1288.

Hu, H., Wen, Y., Chua, T. S., & Li, X. (2014). Toward scalable systems for big data analytics: A technology tutorial. *Access, IEEE*, 2, 652-687.

Huang, J., Newell, S., Huang, J., & Pan, S. L. (2014). Site-shifting as the source of ambidexterity: Empirical insights from the field of ticketing. *The Journal of Strategic Information Systems*, 23(1), 29-44.

Hurwitz, J., Nugent, A., Hapler, F., & Kaufman, M. (2013). *Big Data for Dummies*. Hoboken, New Jersey: John Wiley & Sons.

Igira, F. T. 2008. The situatedness of work practices and organizational culture: implications for information systems innovation uptake. *Journal of Information Technology*, 23(2), 79-88.

Işık, Ö., Jones, M. C., & Sidorova, A. (2013). Business intelligence success: The roles of BI capabilities and decision environments. *Information & Management*, 50(1), 13-23.

Jagadish, H. V., Gehrke, J., Labrinidis, A., Papakonstantinou, Y., Patel, J. M., Ramakrishnan, R., & Shahabi, C. (2014). Big data and its technical challenges. *Communications of the ACM*, 57(7), 86-94.

Jensen, T., & Aanestad, M. (2007). Hospitality and hostility in hospitals: A case study of an EPR adoption among surgeons. *European Journal of Information Systems*, 16(6), 672-680.

Kallinikos, J., & Tempini, N. (2014). Patient data as medical facts: Social media practices as a foundation for medical knowledge creation. *Information Systems Research*, 25(4), 817-833.

Karimi, J., Somers, T.M., & Bhattacherjee, A. (2007). The role of information systems resources in ERP capability building and business process outcomes. *Journal of Management Information Systems*, 24(2), 221-260.

Kohli, R., & Grover, V. (2008). Business value of IT: An essay on expanding research directions to keep up with times. *Journal of the Association for Information Systems*, 9(1), 23-39.

Kowalczyk, D. W. I. M., & Buxmann, P. (2014). Big data and information processing in organizational decision processes. *Business & Information Systems Engineering*, 6(5), 267-278.

Krippendorff, K. (2004). *Content Analysis: An Introduction to Its Methodology* (2nd ed.). London: Sage Publications.

Krippendorff, K. (2012). *Content Analysis: An Introduction to its Methodology*. Sage Press.

Kung, L., Kung, H. J., Jones-Farmer, A., & Wang, Y. (2015). Managing Big Data for Firm Performance: a Configurational Approach. In *Proceeding of the Twenty-First Americas Conference on Information Systems (AMCIS 2015)*, Puerto Rico.

Kwon, O., Lee, N., & Shin, B. (2014). Data quality management, data usage experience and acquisition intention of big data analytics. *International Journal of Information Management*, 34(3), 387-394.

LaValle, S., Lesser, E., Shockley, R., Hopkins, M. S., & Kruschwitz, N. (2011). Big data, analytics and the path from insights to value. *MIT Sloan Management Review*, 52(2), 21-31.

Lucas, H. C. Jr., Agarwal, R., Clemons, E. K., El Sawy, O. A., & Weber, B. 2013. Impactful research on transformational information technology: An opportunity to inform new audiences. *MIS Quarterly*, 37(2), 371-382.

Mantzana, V., Teistocleous, M., Irani, Z., & Morabito, V. (2007). Identifying healthcare actors involved in the adoption of information systems. *European Journal of Information Systems* 16, 91-102.

Markus, M. L., & Benjamin, R. I. (1997). The magic bullet theory in IT-enabled transformation. *Sloan Management Review*, 38(2), 55-68.

Mata, F. J., Fuerst, W. L., & Barney, J. B. (1995). Information technology and sustained competitive advantage: A resource-based analysis. *MIS Quarterly*, 19(4), 487-505.

Melville, N., Kraemer, K., & Gurbaxani, V. (2004). Review: information technology and organizational performance: An integrative model of IT business value. *MIS Quarterly*, 28(2), 283-322.

Meyer, A. D., & Goes, J. B. (1988). Organizational assimilation of innovations: A multilevel contextual analysis. *Academy of Management Journal*, 31(4), 897-923.

Miller, R. H. (1996). Health system integration: a means to an end. *Health Affairs*, 15(2), 92-106.

Minichiello, V., Aroni, R., Timewell, E., & Alexander, L. (1990). *In-Depth Interviewing: Researching People*. Hong Kong: Longman Cheshire.

Mueller, B., Viering, G., Legner, C., & Riempp, G. (2010). Understanding the economic potential of service-oriented architecture. *Journal of Management Information Systems*. 26(4), 145-180.

Murdoch, T. B., & Detsky, A. S. (2013). The inevitable application of big data to health care. *The Journal of American Medical Association*, 309(13), 1351-1352.

Negash, S. 2004. Business intelligence. *Communications of the Association for Information Systems*, 13, 177-195.

Nicolini, D., Powell, J., Conville, P., & Martinez-Solano, L. (2008). Managing knowledge in the healthcare sector. A review. *International Journal of Management Reviews*, 10(3), 245-263.

Oborn, E., Barrett, M., & Davidson, E. (2011). Unity in diversity: Electronic patient record use in multidisciplinary practice. *Information Systems Research*, 22(3), 547-564.

Ogino, S., Galon, J., Fuchs, C. S., & Dranoff, G. (2011). Cancer immunology—analysis of host and tumor factors for personalized medicine. *Nature Reviews Clinical Oncology*, 8(12), 711-719.

Pavlou, P. A., & El Sawy, O. A. (2006). From IT leveraging competence to competitive advantage in turbulent environments: The case of new product development. *Information Systems Research*, 17(3), 198-227.

Peppard, J., Galliers, R. D., & Thorogood, A. (2014). Information systems strategy as practice: Micro strategy and strategizing for IS. *The Journal of Strategic Information Systems*, 23(1), 1-10.

Peppard, J., Weill, P., & Daniel, E. (2007). Managing the realization of business benefits from in investments. *MIS Quarterly Executive*, 6(1), 1-11.

Phillips-Wren, G., Iyer, L. S., Kulkarni, U., & Ariyachandra, T. (2015). Business analytics in the context of big data: A roadmap for research. *Communications of the Association for Information Systems*, 37(1), 23.

Raghupathi, W., & Raghupathi, V. (2014). Big data analytics in healthcare: Promise and potential. *Health Information Science and Systems*, 2(1), 3.

Riabacke, M., Danielson, M., & Ekenberg, L. (2012). State-of-the-art prescriptive criteria weight elicitation. *Advances in Decision Sciences*, 2012, 1-24.

Roski, J., Bo-Linn, G., & Andrews, T. (2014). Creating value in health care through big data: Opportunities and policy implications. *Health Affairs*, 33(7), 1115-1122.

Rowley, J. (2002). Using case studies in research. *Management Research News*, 25(1), 16-27.

Russom, P. (2011). *Big Data Analytics*. TDWI Best Practices Report, Fourth Quarter.

Russo-Spena, T., & Mele, C. (2012). ‘Five co-s’ in innovating: a practice-based view. *Journal of Service Management*, 23(4), 527-553.

Saaty, T.L. (1980). *The Analytic Hierarchy Process*. New York: McGraw-Hill.

Sackett, D. L., Rosenberg, W. M., Gray, J. A., Haynes, R. B., & Richardson, W. S. (1996). Evidence based medicine: What it is and what it isn't. *BMJ: British Medical Journal*, 312(7023), 71.

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

Schatzki, T. R. (2001). Introduction: Practice Theory. In Schatzki, T. R., Knorr Cetina, K. and von Savigny, E. (eds), *The Practice Turn in Contemporary Theory*, London: Routledge.

Schatzki, T. R. (2005). Peripheral vision: The sites of organizations. *Organization Studies,* 26(3), 465-484.

Schilling, J. (2006). On the pragmatics of qualitative assessment: Designing the process for content analysis. *European Journal of Psychological Assessment*, 22(1), 28-37.

Schleidgen, S., Klingler, C., Bertram, T., Rogowski, W. H., & Marckmann, G. (2013). What is personalized medicine: sharpening a vague term based on a systematic literature review. *BMC Medical Ethics*, 14(1), 55.

Schneeweiss, S. (2014). Learning from big health care data. *The New England Journal of Medicine*, 370(23), 2161-2163.

Schouten, P. (2013). Big data in health care: solving provider revenue leakage with advanced analytics. *Healthcare Financial Management Association, 67*(2), 40-42.

Schroeck, M., Shockley, R., Smart, J., Romero-Morales, D., & Tufano, P. (2012). *Analytics: The Real-World Use of Big Data: How Innovative Enterprises Extract Value from Uncertain Data*. New York: IBM Global Service.

Schryen, G. (2013). Revisiting IS business value research: what we already know, what we still need to know, and how we can get there. *European Journal of Information Systems*, 22(2), 139-169.

Scott, W. R., Ruef, M., Mendel, P., & Caronna, C. (2000). *Institutional Change and Healthcare Organizations: From Professional Dominance to Managed Care*, Chicago: University of Chicago Press.

Seddon, P. B., Constantinidis, D., & Dod, H. (2012). How does business analytics contribute to business value? In *Proceeding of Thirty Third International Conference on Information Systems*, Orlando, USA.

Shah, N.D., & Pathak, J. (2014). Why Health Care May Finally Be Ready for Big Data. Retrieved January 12 2015 from Harvard Business Review: https://hbr.org/2014/12/why-health-care-may-finally-be-ready-for-big-data.

Shang, S., & Seddon, P. B. (2002). Assessing and managing the benefits of enterprise systems: The business manager's perspective. *Information Systems Journal*, 12(4), 271-299.

Shanks, G., & Bekmamedova, N. (2012). Achieving benefits with business analytics systems: an evolutionary process perspective. *Journal of Decision Systems*, 21(3), 231-244.

Sharma, R., Mithas, S., & Kankanhalli, A. (2014). Transforming decision-making processes: a research agenda for understanding the impact of business analytics on organisations. *European Journal of Information Systems*, 23(4), 433-441.

Shmueli, G., & Koppius, O. (2010). Predictive analytics in information systems research. *MIS Quarterly*, 35(3), 553-572.

Simpao, A. F., Ahumada, L. M., & Rehman, M. A. (2015a). Big data and visual analytics in anaesthesia and health care. *British Journal of Anaesthesia*, 115(3):350-356.

Simpao, A. F., Ahumada, L. M., Desai, B. R., Bonafide, C. P., Gálvez, J. A., Rehman, M. A., ... & Shelov, E. D. (2015b). Optimization of drug–drug interaction alert rules in a pediatric hospital's electronic health record system using a visual analytics dashboard. *Journal of the American Medical Informatics Association*, 22, 361-369.

Srinivasan, U., & Arunasalam, B. (2013). Leveraging big data analytics to reduce healthcare costs. *IT Professional*, 15(6), 21-28.

Storage Networking Industry Association (2009). *The Information Lifecycle Management Maturity Model*. Storage Networking Industry Association Press.

Straus, S., Richardson, W.S., Glasziou, P. & Haynes, R.B. (2005). *Evidence-based Medicine: How to Practice and Teach EBM (3rd ed.)*. Edinburgh: Churchill Livingstone.

Strauss, A., & Corbin, J. (1998). *Basics of Qualitative Research: Techniques and Procedures for Developing Grounded Theory (2nd ed.)*. Thousand Oaks, CA: Sage Publications.

Tallman, S., & Chacar, A. S. (2011). Knowledge accumulation and dissemination in MNEs: A practice-based framework. *Journal of Management Studies*, 48(2), 278-304.

Tamm, T., Seddon, P., & Shanks, G. (2013). Pathways to value from business analytics. In *Proceeding of Thirty Fourth International Conference on Information Systems*, Milan, Italy.

Tiefenbacher, K., & Olbrich, S. (2015). Increasing the value of big data projects - investigation of industrial success stories. In *Proceeding of 2015 48th Hawaii International Conference on System Sciences*, Kauai, Hawaii.

Trkman, P. McCormack, K. De Oliveira, M. P. V., & Ladeira, M. B. (2010). The impact of business analytics on supply chain performance. *Decision Support Systems*, 49(3), 318-327.

Venkatraman, N. (1994). IT-enabled business transformation: From automation to business scope redefinition. *Sloan Management Review*, 35(2), 73-87.

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

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

Wang, Y., Kung, L., Ting, C., & Byrd, T. A. (2015). Beyond a technical perspective: understanding big data capabilities in health care. In System Sciences (HICSS), 2015 48th Hawaii International Conference on (pp. 3044-3053). IEEE.

Ward, M. J., Marsolo, K. A., & Froehle, C. M. (2014). Applications of business analytics in healthcare. *Business Horizons*, 57(5), 571-582.

Watson, H. J. (2014). Tutorial: big data analytics: Concepts, technologies, and applications. *Communications of the Association for Information Systems*, 34, 1247-1268.

Weber, R. P. (1990). Basic content analysis. Newburry Park, CA: Sage Publications.

Webster, J., & Watson, R. T. (2002). Analyzing the past to prepare for the future: writing a literature review, *MIS Quarterly*, 26(2), xiii-xxiii.

Whittington, R. (2014). Information systems strategy and strategy-as-practice: a joint agenda. *The Journal of Strategic Information Systems*, 23(1), 87-91.

Winter, R., Gilbert, R., & Davis, J. R. (2013). *Big Data: What Does It Really Cost*? Cambridge, MA: Winter Corporation.

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

Yin, R.K. (2000). Rival explanation as an alternative to reforms as "experiments". In L. Bickman (Ed.), *Validity and Social Experimentation*: *Donald Campbell's Legacy*. Thousand Oaks, CA: Sage Publication, Inc.

Yin, R.K. (2008). *Case Study Research: Design and Methods*. Sage Publications.

Essay 2: Business Analytics-Enabled Decision Making Effectiveness through Absorptive Capacity: Evidence from Healthcare Industries

Introduction

Business analytics (BA) is increasingly advocated as an important strategic information technology (IT) investment for many healthcare organizations. BA systems encompass a number of different analytics techniques such as descriptive analytics and predictive analytics (Delen, 2014) that can be used to support evidence-based decision-making and action-taking (Chen et al., 2012; Watson, 2014). Due to the unique characteristics of the healthcare field, implementing BA is challenging for healthcare entities seeking to adopt a thoughtful, holistic approach to data analysis and knowledge management and thus enhances organization performance (Ghosh & Scott, 2011; Raghupathi & Raghupathi, 2014).

Several research gaps have been found to prevent healthcare practitioners and academics from fully embracing BA. First, an increasing number of studies have demonstrated the potential of this technology for providing tailored, context-sensitive information to guide clinical practice (e.g., Bardhan et al., 2015; Halamka, 2014; Spruit et al., 2014). However, the constantly growing body of academic research on BA is mostly technology oriented (Wamba et al., 2015). Given that the resulting contribution to business value remains poorly understood, it is harder for healthcare managers to alter their mindset to adopt BA technologies (Murdoch & Detsky, 2013; Shah & Patak, 2014).

Second, despite leveraging business analytics to derive clinical decisions is emerging as a top priority for healthcare organizations, only 42% of healthcare organizations surveyed have adopted rigorous analytics approaches to support their decision-making processes and just 16%

have substantial experience using analytics across a broad range of functions (Cortada et al., 2012). Many healthcare organizations are suffering from the lack understanding of how to transform clinical data (e.g., electronic health records and insurance claims/billing) into insights, knowledge, and informed decisions (Raghupathi & Raghupathi, 2014; Ward et al., 2014).

Third, a number of studies have explored the impact of BA in terms of its potential for harvesting data-driven insights, supporting evidence-based medicine, and improving the quality of care at a lower cost (e.g., Bates et al., 2014; Foshay & Kuziemsky, 2014; Halamka, 2014; Srinivasan & Arunasalam, 2013). By using single or multiple case studies, these studies could provide practical evidence to support healthcare organizations seeking to implement business analytics initiatives, but their findings have not been collected into a single comprehensive framework, or validated on a broader empirical basis.

Finally, previous studies have developed the BA models to demonstrate the managerial, economic, and strategic impacts of BA from the different theoretical perspectives. Yet, these are generic and do not meet the healthcare industry's particular requirements (Brooks et al., 2015; Foshay & Kuziemsky, 2014). There is no BA success model that would encourage healthcare organizations to recognize the business value of BA in healthcare settings and guide them through the process to effectively utilize BA for decision making in clinical settings.

Based on these gaps identified from the existing literature, we attempt to focus on two important issues, which have not yet been addressed in research literature. First, what capabilities (technical or non-technical) can be created from the use of business analytics that healthcare organizations should acquire to succeed in driving sound decisions (Ghosh & Scott, 2011; Phillips-Wren et al., 2015). Second, what organizational capabilities enable healthcare organizations to effectively deliver knowledge, triggered by the use of BA systems, to various decision makers and other stakeholders (Ghosh & Scott, 2011; Sharma et al., 2014; Phillips-Wren et al., 2015). Thus, the objective of this study has been to advance the theory in this area and develop a better understanding of its practical impacts by examining how BA capabilities can contribute to decision making effectiveness through organizational capabilities in healthcare organizations.

To this end, we begin by conceptualizing the multi-dimensional role of BA capabilities, which are shaped by a set of technological BA architectural components (i.e., data aggregation, data analysis, and data interpretation) based on the resource based view (RBV) and the IT capability literature (Bharadwaj, 2000; Santhanam & Hartono, 2003). We then follow the dynamic capability view (Pavlou & El Sawy, 2006; 2010) and the arguments from prior BA literature (Cao et al., 2015; Popovič et al., 2012; Trkman et al., 2010) to consider a mediating role between BA related constructs and organizational performance since IT alone do not unequivocally facilitate organizational performance (El Sawy et al., 2010). Specifically, to capture the learning capabilities of an organization, this study uses absorptive capacity in the relationship between BA capabilities and decision-making effectiveness on the grounds that it plays an intermediary role in transforming knowledge obtained from the use of BA systems into a useful decision-making resource for healthcare organizations. To summarize, our research model is designed to answer the following research question: *Do business analytics capabilities improve decision-making effectiveness through the mediating role of absorptive capacity in healthcare?*

The next section of this paper reviews the current research in this area, focusing specifically on the development of models for successful BA implementations. Rather than exhaustively include every study in the relevant fields, our goal for the review is to highlight those that directly inform our study and then discuss the gaps in the extant literature that we seek to fill. We then move on to examine the theoretical background for BA capability, absorptive capacity, and decision-making effectiveness to create a basis for developing a research model with a series of hypotheses about the relationships between these proposed constructs. After describing our research methodology and presenting the results, we conclude by discussing our findings and their implications.

Current Research on Exploring Value from Business Analytics

There have been a number of studies focused on developing BA success models that are generally grounded on information processing view (IPV) and resource-based theory (RBT). This literature review follows a concept-centric approach (Webster & Watson, 2002) to classify the studies by the different theoretical perspectives (i.e., IPV and RBT), as summarized in Appendix A in this first essay.

IPV posits that "the greater the task performance, the greater the amount of information that must be processed among decision-makers during task execution in order to achieve a given level of performance" (Galbraith, 1974, p. 28). Drawing on an IPV (Galbraith, 1974), several studies treat BA as an emerging technology that helps organizations process huge amounts of data to acquire meaningful insights that they can then transform into organizational knowledge and actionable decisions (Cao et al., 2015; Kowalczyk & Buxmann, 2014; Trkman et al., 2010). To enhance the quality of this transformation, researchers argue that organizations should design their organizational structure, mechanism, and business processes taking into account data analysis processes that can potentially reduce the environmental uncertainty and ambiguity of the problem context (Kowalczyk & Buxmann, 2014; Sharma et al., 2014). For example, Trkman et al. (2010) report that firms that have the ability to analyze and utilize their information within the different stages of the supply chain (i.e., plan, source, make, and deliver) enjoy a superior supply chain performance as a result. Cao and colleagues (2015) have found that utilizing BA influences information processing capability through the mediation of a data-driven environment, which in turn has a positive effect on decision-making effectiveness. Although these studies allow us to understand how business decisions are made through the joint effect of business analytics and information processing mechanisms, they mostly focus on exploiting the use of information to improve decision-making processes and outcomes and seldom go on to consider what capabilities can be created from the use of BA technical or non-technical resources that organizations could acquire to successfully drive business value (Phillips-Wren et al., 2015).

Grounded in the theoretical lens of the RBV (Barney, 1991; 2001), a number of studies have argued that a firm's unique business analytics capability can be constructed in terms of either the configurations of available business analytics technological resources (e.g., Chae et al., 2014; Kwon et al., 2014; LaValle et al., 2011; Wixom et al., 2013) or the synergetic combination of valuable, rare, imperfectly imitable and non-substitutable organizational resources (e.g., Işık et al., 2013; Seddon et al., 2012; Tamm et al., 2013). For example, Wixom et al. (2013) identify two key business analytics capabilities – speed to insight and pervasive use – and their underlying dimension from BA resources as playing a role in maximizing business value in the fashion retail industry.

In addition to BA's technical capabilities, analytics personnel (including analytical executives, analytical professionals, and analytics employees) (Seddon et al., 2012; Tamm et al., 2013) play a vital role in enabling BA capability that enhances organizational performance. By analyzing BA success stories from IT vendors, for instance, Seddon et al. (2012) develop a short-term BA project success model that identifies the critical resource-based factors leading to organizational benefits. In this model, BA capabilities (i.e., the functional fit of BA tools and ready availability of high-quality data), analytical personnel, and overcoming organizational inertia are the predictors of successful BA improvement projects. However, there is an ongoing debate in the IS literature regarding whether IT-enabled constructs developed specifically for IT resources confer or facilitate competitive advantage directly or indirectly (Devaraj & Kohli, 2003; Wade & Hulland, 2004). The literature on the business value of IT emphasizes that IT resources alone do not unequivocally facilitate competitive advantage (El Sawy et al., 2010). Moreover, strategic management scholars have criticized the weakness of RBV in elucidating the missing link in the relationship between resource-based constructs and organizational performance (Bromiley & Rau, 2014; Melville et al., 2004).

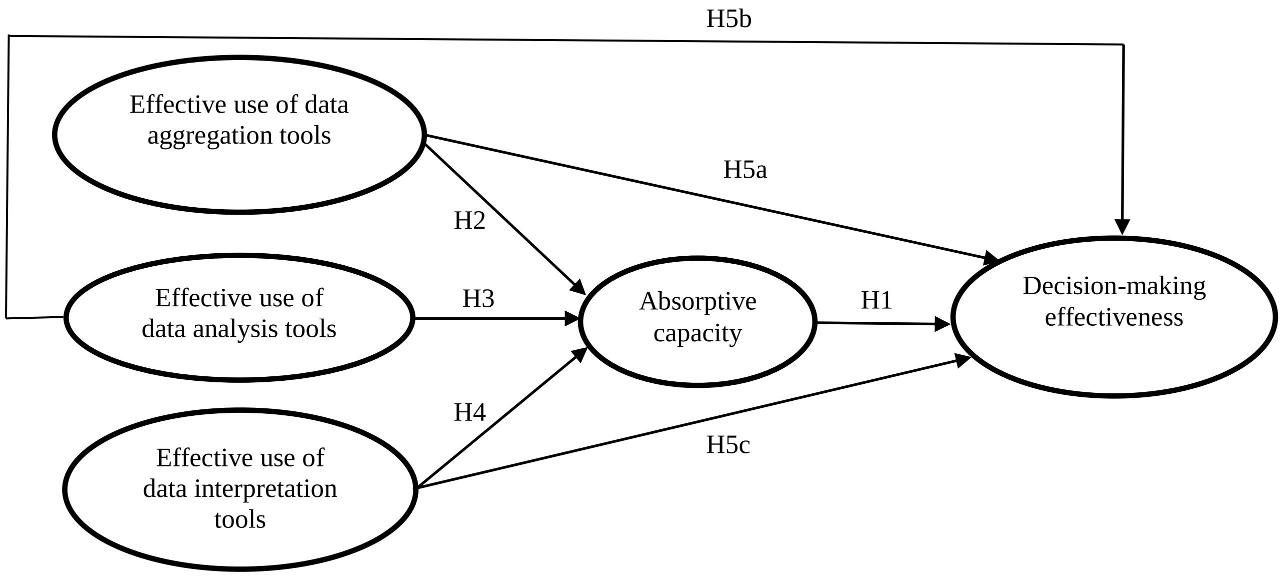
In an attempt to address these known pitfalls of IPV and RBV, we integrate the RBV and dynamic capability view to build our research model as no one single theory covers all aspects. Specifically, we develop a research model to represent the mechanisms by which BA capabilities (i.e., the effective use of data warehouse tools, analytics tools, and data visualization tools) in healthcare units can be shown to indirectly influence decision making effectiveness through a key mediating link: absorptive capacity. In the next section, we will present the research model and hypotheses development of this study.

Research Model and Hypothesis Development

Drawing on the resource based view (Barney, 1991; 2001) and IT capability literature (e.g., Bharadwaj, 2000; Karimi et al., 2007), we first conceptualize BA capability by arguing that BA resources – that is, its BA architectural components (i.e., data aggregation, data analysis, and data interpretation) can create BA-specific capabilities. IT capability literature generally adopts a resource-based theory to argue that a firm's unique IT capability can be constructed by the configurations of its available tangible and intangible IT resources or the synergetic combination of its non-valuable, rare, imperfectly imitable and non-substitutable (VRIN) resources (Santhanam & Hartono, 2003). IT capability refers to "the ability to mobilize and deploy IT-based resources in combination or copresent with other resources and capabilities" (Bharadwaj, 2000, p. 171). Previous studies have regarded IT capability as a multi-dimensional construct. From a system functionality perspective, Pavlou and El Sawy (2006) propose three key dimensions of IT capability that can be identified from new product design systems: effective use of project and resource management systems, effective use of knowledge management systems, and effective use of cooperative work systems. With this logic, BA capability could be a specific type of IT capability, defined as the ability to acquire, store, process and analyze large amount of data in various forms, and then deliver meaningful information to users that allows them to discover business values and insights in a timely fashion (Davenport & Harris, 2007). BA capability can be created or reinforced through the application of its architectural components.

We then follow dynamic capability view that explains how organizations integrate, reconfigure, gain and renew resources to match rapidly-changing market environments (Eisenhardt & Martin, 2000; Helfat & Peteraf, 2003; Teece et al., 1997). Dynamic capability is a firm's organizational ability to sense and shape opportunities and threats, to seize market opportunities and to maintain competitiveness (Barreto, 2010; Teece, 2007). In the existing literature, absorptive capacity is viewed as a specific type of dynamic capability that enables organizational knowledge management (Liu et al., 2013). Pavlou and El Sawy (2006) and Roberts et al. (2012) agree, arguing that absorptive capacity serves as a complement to IT capability in creating business value and emphasizing that obtaining capabilities from the use of IT to increase organizational performance cannot be guaranteed unless organizations have sufficient capacity to identify, absorb, transform, and exploit the knowledge that is generated from IT. Indeed, leveraging business analytics for gaining business value is not a simple technical issue per se, but a managerial and strategic one, which requires organizations to undergo adjustments or even dramatic changes regarding workflows, leadership, knowledge management, and organizational culture (Mcafee & Brynjolfsson, 2012). Some researchers suggest that healthcare organizations must understand the ways how the analytic tools can be used to obtain medical knowledge and transform them into clinical practices that allow them to create a high quality evidence-based medicine (Brooks et al., 2015; Schneeweiss, 2014). Without such an ability to absorb and deliver knowledge, healthcare organizations may not make accurate decisions through the use of BA systems.

Based on the dynamic capability view, absorptive capacity can be conceptualized as a higher-order organizational capability (Liu et al., 2013; Roberts et al., 2012), while IT capabilities can be viewed as lower-order capabilities that triggering by higher-order capabilities (Pavlou & El Sawy, 2006; 2010). In this view, absorptive capacity is widely defined as higher-order capabilities that enable firms to identify, assimilate, and exploit lower-order capabilities (e.g., IT capability and operational capability) to help organizations acquire and sustain a competitive advantage (Cohen & Levinthal, 1990; Grewal & Slotegraaf, 2007; Zahra & George, 2002). Following this logic, this study proposes that BA capabilities are lower-order capabilities that can be leveraged to develop absorptive capacity that, in turn, affect decision-making effectiveness. Figure 1 shows the research model.



The proposed research model

Figure 1. Achieving decision making effectiveness through business analytics

Decision Making Effectiveness

In the IS literature, decision-making effectiveness is an important indicator of IS success. Decision-making effectiveness is generally viewed as the dependent variable for IS success (DeLone & McLean, 1992) and is defined as the users' perceptions towards decision-making satisfaction. Early researchers in this area (e.g., Meador et al., 1984; Sanders & Courtney, 1985) used decision-making effectiveness to measure the performance of decision support systems. Despite firms implementing various decision support systems to pursue the delivery of information to decision-makers and improve their decision-making effectiveness, the benefits have not had as much impact as anticipated (Sharma & Yetton, 2003). Decision support systems focus on using a consistent set of metrics to measure past performance and provide managers with structured, periodic reports to guide business planning (Power, 2008). However, these traditional decision support systems may not be capable of supporting timely decision-making that enables managers to quickly respond to environmental turbulence and competitive markets in health care.

To address this, several researchers have suggested that the productivity and quality of decision-making can be improved with the aid of advanced data analysis techniques. For example, Popovič et al. (2012) argue that a mature business intelligence system with strong analytical capabilities and data integration, along with knowledge workers who are capable of making full use of complex business intelligence systems, can provide sufficient information to markedly improve decision-making processes. In the same vein, Cao et al. (2015) demonstrate that the use of BA, specifically focusing on its analytical and decision support tools, through the mediation of a data-driven environment, significantly affects information processing capability, which in turn results in enhanced decision making effectiveness.

In healthcare context, Ghosh & Scott (2011) describe how analytic capabilities facilitate data-driven decision making. Their case study shows that Veterans Health Administration's (VHA) BA systems support the physicians' day-to-day clinical practices, such as assessing the riskiness of a certain surgical procedure by providing the outputs displayed in the dashboards and metrics. BA systems also allow aggregating patient data to establish measurable improvements that help healthcare managers allocate resources (e.g., determine the resource utilization for the facility and geographic distribution of patients support service needed) and choose future treatments and policies (e.g., assess the outcomes of policy initiatives and develop medical protocols).

From the BA literature, decision-making effectiveness can be achieved by boosting the speed of a decision and the extent to which organizations understand their customers (Cao et al., 2015; LaValle et al., 2011; Wixom et al., 2013). Both outcomes have been emphasized in the context of analytics-based healthcare systems and individually linked to improved quality of patient care (Barjis et al., 2013; Foshay & Kuziemsky, 2014). Therefore, this study chose enhanced decision-making effectiveness as signifying BA success in the healthcare context. The following sections describe the roles of BA capabilities and absorptive capacity, which are proposed to influence decision-marking effectiveness.

Business Analytics Capabilities

Following Pavlou and El Sawy's (2006) reasoning, the key dimensions of BA capability can be identified from the tools and functionalities of BA systems. To this end, we reviewed the relevant academic literature (e.g., Raghupathi & Raghupathi, 2014; Ward et al., 2014), technology tutorials (Hu et al., 2014; Watson, 2014), and case descriptions regarding applying BA systems in healthcare settings. Our starting point was Ward et al.'s (2014) proposed BA architectural framework for health care that elucidates how decisions are made in terms of four architectural layers that begin with data generation and continue through data extraction and data analysis to visualization and reporting, listing the tools and functionalities that are used in each architectural layer. With these dimensions in mind, over 60 big data implementation cases from diverse resources such as major IT vendors, academic journal databases, and healthcare institute reports were reviewed to include, integrate, or drop the items. This review generally affirmed Ward et al.'s framework, apart from the need to integrate data generation and data extraction under a single dimension – data aggregation – because BA systems typically use data warehousing tools to capture, aggregate and ready data from various sources for processing (Raghupathi & Raghupathi, 2014). Based on the results of this review, we propose three key dimensions of BA capability in healthcare: (1) the effective use of data aggregation tools, (2) the effective use of data analysis tools, and (3) the effective use of data interpretation tools, as described below in more detail and summarized in Table 1.

Table 1. Key Constructs of BA Capability

BA systems	Tools	Key functionalities	Effective use of BA systems
Data aggregation tools	• Middleware • Data warehouse • Extract-transform-load (ELT) tools • Hadoop distributed file system (HDFS) • NoSQL database	• Extracting data from large amounts of data • Transforming data into standard formats • Data storage	• Collect data from external sources and from various systems throughout the healthcare units • Make data consistent, visible and easily accessible for analysis • Store data into appropriate databases
Data analysis tools	• Apache Hadoop/Map Reduce • Statistical analysis • OLAP • Predictive modeling • Social media analytics • Machine learning • Text mining/NLP	• Processing large amounts of unstructured and semi-structured data across a massively parallel cluster of servers using Hadoop Map/Reduce • Real-time analysis by utilizing stream computing • In-database analytics for analyzing the structure of patient records • Social media analytics for analyzing web data	• Identify important business insights to improve costly healthcare services such as unnecessary diagnostic tests and treatments • Predict pattern of care to quickly response patient needs • Analyze data in near-real or real time that allows to quickly respond to unexpected events • Analyze social media data such as patient subjective opinions, medicine recommendations and ratings to understand current trends in a large population
Data interpretation tools	• Visual dashboards/systems • Reporting systems/interfaces	• General summary of data • Visualization reporting • Real-time reporting	• Provide systemic and comprehensive reporting mechanisms to help recognize feasible opportunities for improvement • Support data visualization that enables users to easily interpret results

			• Provide near-real or real time information on health care operations and services within health care facilities and across health care systems

Effective use of data aggregation tools

Data aggregation tools are capable of transforming different types of healthcare data (e.g., electronic health records; EHRs, diagnostic or monitoring instrument data, web and social media data, insurance claims/transaction data, pharmacy data, patient-generated data) into a data format that can be read by the data analysis platform. As Raghupathi and Raghupathi (2014) stated, data is intelligently aggregated by three key functionalities in data aggregation tools: acquisition, transformation, and storage.

The primary goal of data acquisition is to collect data from external sources and all the various system components across the healthcare organization. During the data transformation process, transformation engines move, clean, split, translate, merge, sort, and validate the data, as needed. Structured data such as that typically contained in an eclectic medical record is extracted from EHR systems and converted into a specific standard data format, sorted by specified criterion (e.g., patient name, location, or medical history), and then the record validated against data quality rules. Finally, the data are loaded into target databases such as Hadoop distributed file systems (HDFS) or stored in a Hadoop cloud for further processing and analysis. The data storage principles are established based on compliance regulations, data policies and access controls, and data storage methods can be implemented and completed in batch processes or in real time. Since these three functionalities support health care service in value-adding ways, the effective use of data aggregation tools is viewed as a key element of BA capability in health care.

Effective use of data analysis tools

Data analysis tools process all kinds of data and perform appropriate analyses to harvest insights (Wald et al., 2014). This is particularly important for transforming patient data into meaningful information that supports evidence-based decision making and useful practices for healthcare organizations. The simple taxonomy of analytics developed by Delen (2014) lists three main kinds of analytics, descriptive, predictive, and prescriptive, each of which is distinguished by the type of data and the purpose of the analysis.

Descriptive analytics has been widely used in both business intelligence systems and BA systems (Watson, 2014). The methods and algorithms for descriptive analytics such as online analytics processing (OLAP) reporting, excel-based business intelligence application, and data mining support the analysis of structured data within a relational data warehouse that provides the ability to describe the data in summary form for exploratory insights and answer “What has happened in the past?” questions for managers (Phillips-Wren et al., 2015; Watson, 2014). In hospital settings, descriptive analytics is useful because it allows healthcare practitioners to understand past patient behaviors and how these behaviors might affect outcomes from their EHR database. It also provides high-speed parallel processing, scalability, and optimization features geared toward BA, and offers a private and secure environment for confidential patient records (Wang et al., 2015).

Predictive analytics allows users to predict or forecast the future for a specific variable based on probability estimation (Phillips-Wren et al., 2015; Watson, 2014). Hadoop/MapReduce, one of the most commonly used predictive analytics-based software products, integrates analytical approaches such as natural language processing (NLP), text mining, and natural networks in a massively parallel processing (MPP) environment. In general, predictive analytics provides the ability to cost-effectively process large volumes of data in batch form, allowing the analysis of both structured and unstructured data as well as supporting data processing in near real time or real time (Belle et al., 2015). More importantly, predictive analytics enables users to develop predictive models in a flexible and interactive manner to identity causalities, patterns and hidden relationships between the target variables for future predictions. Applying this to a healthcare context, predictive analytics helps managers disentangle the complex structure of clinical cost, identify best clinical practices, and gain a broader understanding of future healthcare trends based on knowledge of patients' lifestyles, habits, disease management and surveillance (Groves et al., 2013). For example, predicative analytics supports Beth Israel Deaconess Medical Center's home health care service by predicting patient illness, quickly deploying nurses to supplement care no matter where the patient suffers a health emergency, thus avoiding expensive emergency department visits, and collaborating with local healthcare providers to coordinate care (Halamka, 2014). Predictive analytics also can be used to analyze social media data. Prior research has indicated that this analysis could benefit a healthcare organization in various ways, including helping track and even predict the course of illness through a population, providing non-official channels for disease reporting, and facilitating conversations and interactions with patients (Ward et al., 2014).

Prescriptive analytics is a relatively new kind of analytics that uses a combination of optimization-, simulation-, and heuristics-based predictive modeling techniques such as business rules, algorithms, machine learning and computational modeling procedures (Delen, 2014). Whereas predictive analytics suggests "what will occur in the future" (Watson, 2014, p. 1251), prescriptive analytics offers optimal solutions or possible courses of action to help users decide what to do in the future (Phillips-Wren et al., 2015; Watson, 2014). Prescriptive analytics continually re-predicts and automatically improves prediction accuracy by importing and incorporating new datasets (a combination of structured and unstructured data and business rules) to aid decision makers in solving problems (Riabacke et al., 2012).

Combining these functionalities of data analysis can help increase the efficiency of health care delivery, and we thus proposed the effective use of data analysis tools as a key dimension of BA capability.

Effective use of data interpretation tools

Data interpretation tools can be used to produce reports about daily healthcare services to aid managers' decisions and actions. Three key functionalities are involved. The first functionality yields general clinical summaries such as historical reporting, statistical analyses, and time series comparisons and can be utilized to provide a comprehensive view that supports the implementation of evidence-based medicine (Ghosh & Scott, 2011), provides advanced warnings for disease surveillance (Jardine et al., 2014), and guides diagnostic and treatment decisions (Fihn et al., 2014).

Second, data visualization, which is a critical BA feature, facilitates the extraction of meaning from external data by creating helpful visualizations of the information, generally in the form of interactive dashboards and charts. In healthcare, these visualization reports support physicians and nurses' daily operations and help them to make faster and more rational evidence-based decisions (Roski et al., 2014). For example, a Dutch long-term care institution has visualized the number of incidents, the locations where the incidents occurred, and the type of physical damage that resulted by mining a collection of 5,692 incidents over a certain time period (Spruit et al., 2014). Displaying frequency tables in the form of visual dashboards has enabled this Dutch long-term care institution to improve patient safety throughout the hospital.

Third, real-time reporting, such as alerts and proactive notifications, real time data navigation, and operational key performance indicators (KPIs) can be sent to interested users or made available in the form of dashboards in real time. Since these three functionalities support clinical decision making, the effective use of data interpretation tools is viewed as a key element of BA capability.

Absorptive capacity

Absorptive capacity was conceptualized by Cohen and Levinthal (1990) to describe how a firm absorbs relevant knowledge. In the context of IS, Lichtenthaler (2009) defines it as the ability to assimilate and transform valuable IS knowledge, or to combine new knowledge with existing knowledge by communicating with other organizational members. Cohen and Levinthal (1990) originally identify three dimensions of absorptive capacity: identification, assimilation and exploitation. This was later expended to four dimensions: acquisition, assimilation, transformation, and exploitation of knowledge (Flatten et al., 2011; Zahra & George, 2002). We follow this extended conceptualization and consider these four capacities together to represent the absorptive capacity of the organization. Acquisition reflects the process of identifying valuable knowledge from external resources, such as conferences, suppliers, and news. Assimilation means the process of understanding or interpreting the meaning of the knowledge, while transformation refers to the integration of new knowledge with current knowledge, thus preparing the knowledge for application (Zahra & George, 2002). Finally, exploitation illustrates the process of using the “integrated” knowledge to improve the organization’s existing performance and generate new value. Together, these four capacities reflect firms' ability to highlight and apply new knowledge, which is critical to organizational performance.

From an organizational learning perspective (Lichtenthaler, 2009), absorptive capacity is believed to be beneficial for firms since it allows them to identify the value of new information gathered from internal and external source, absorb it, and apply it to support their business decisions (Cohen & Levinthal, 1990; Saraf et al., 2013). The IT business value literature also suggests that absorptive capacity acts as a key driver of transforming IT into business value because organizations have to make a considerable effort to acquire and internalize new knowledge from IT (e.g., Joshi et al., 2010; Malhotra et al., 2005; Song et al., 2007). With absorptive capacities, a firm can proactively make proper and fast decisions on business strategies than their competitors (Elbashir et al., 2011; Francalanci & Morabito, 2008). In the context of new product development, for example, firms can make timely decisions related to product development and more effectively commercialize innovative ideas into new products if they can create new knowledge more efficiently than other competitors (Lin et al., 2015). Based on these arguments, we believe that a high level of organizational absorptive capacity enables healthcare organizations to transform clinical data into insights that speed up the decision-making process and enable medical staffs to respond quickly to customer needs. Hence, the following hypothesis was developed:

Hypothesis 1 (H1): Absorptive capacity will have a positive impact on decision-making effectiveness in health care.

The effect of BA capabilities on absorptive capacity

In health care, several studies have reported that BA capability offers several benefits when managing healthcare service compared to traditional decision support systems, including the ability to gather data from current patients to gain useful knowledge for decision-making (Ghosh and Scott, 2011), the ability to predict patient behavior via predictive analytics, and the option to retain valuable customers by providing real-time offers (Bardhan et al., 2015; Srinivasan and Arunasalam, 2013). Although acquiring and extracting knowledge from patient data appears to be a challenge due to the need to preserve privacy and maintain trust in the health infrastructure (Chen et al., 2012; Wickramasinghe and Schaffer, 2006), several studies have explored ways through which BA capabilities can help healthcare organizations improve their absorptive capacity (Wickramasinghe & Schaffer, 2006). First, the effective use of data aggregation tools can track healthcare data from external sources and the system's IT components throughout the organization's units. Healthcare-related data such as activity and cost data, clinical data, pharmaceutical R&D data, patient behavior and sentiment data are commonly collected in real time or near real time from payers, healthcare services, pharmaceutical companies, consumers and stakeholders outside healthcare (Groves et al., 2013). Thus, knowledge related to patient' needs is likely to be acquired when the ability to collect, store, and disseminate the data are sufficient.

Second, since significant clinical knowledge and a deeper understanding of patient disease patterns can be gathered from the analysis of EHRs (Lin et al., 2011), data analysis has become an important tool to identify patterns of care and discover associations from massive healthcare records, thus providing a broad overview for evidence-based clinical practice. In hospital settings, the clinical analysis tools in large longitudinal healthcare databases can be used to identify knowledge about drug risk, for example. By integrating BA algorithms into their legacy IT systems, medical staffs can automatically acquire information relating to drug safety decompensation, and treatment optimization by analyzing warning signals triggered by alarm systems (Bates et al., 2014). In addition to clinical analyses, social media analytics allow healthcare organizations to discover knowledge from online healthcare communities (Fan & Gordon, 2014). Social media and its content generated by social interactions and communications among patients not only makes it possible to explore incredible business values, but can also serve as a vital knowledge base for improving healthcare quality and patient satisfaction.

Third, the effective use of data interpretation tools can yield sharable information and knowledge in the form of historical reports, executive summaries, and drill-down queries in an interoperable BA platform. BA has the potential to equip organizations with the reporting systems they need to harness the mountains of heterogeneous data, information, and knowledge that they routinely gather, disentangle intricate customer networks and develop a new portfolio of business strategies for products and services. For example Premier, a healthcare alliance of approximately 3,000 U.S. hospitals, collects data from different departmental systems and sends it to a central data warehouse. After near-real-time data processing, comprehensive and comparable clinical reports of resource utilization and transaction level cost are generated and used to help hospital managers to recognize emerging healthcare issues such as patient safety and inappropriate medication use.

Given the increasing embeddedness of BA tools in healthcare operational process, the extent to which a healthcare organization can rapidly acquire, assimilate, and exploit knowledge across its boundaries appears to be primarily dependent upon its ability to leverage and implement BA tools, which is reflected in its BA capabilities. Hence, we developed the following set of hypotheses:

Hypothesis 2 (H2): The effective use of data aggregation tools has a positive impact on absorptive capacity in health care.

Hypothesis 3 (H3): The effective use of data analysis tools has a positive impact on absorptive capacity in health care.

Hypothesis 4 (H4): The effective use of data interpretation tools has a positive impact on absorptive capacity in health care.

The mediating role of absorptive capability

Drawing on the dynamic capability view, Pavlou and El Sawy (2006) contend that the pivotal role of dynamic capability, triggered by the effective use of new product development (NPD) systems, has become the source of competitive advantage in the NPD context. Pavlou and El Sawy's study extends RBV by considering the effect of dynamic capability as a mediating factor linking the impact of NPD related systems with competitive advantage. Following this logic, few studies view BA capabilities as lower-order capabilities that enabling the development of higher-order organizational capabilities, such as BA-enabled organizational capabilities and dynamic capabilities (Chasalow & Baker, 2015; Knabke & Olbrich, 2015; Shanks & Bekmanedova, 2012) and adaptive capabilities (Erevelles et al., 2016). In their longitudinal case study of a large financial institution, Shanks and Bekmanedova (2012) found evidence to suggest that BA systems creates firm performance by orchestrating BA enabled organizational capabilities and dynamic capabilities over time. Knabke and Olbrich (2015) investigate that firms' business trends discovered by BA systems can affect data warehouse-based business intelligence (BI) and dynamic BI capabilities, and in turn lead to support decision making. Most recently, Erevelles et al. (2016) integrates RBV with dynamic capability to develop a BA enabled competitive advantage model. Their model not only argues that organizational BA resources allow firms to transform marketing data into consumer insights, but also underscores the realization that dynamic and adaptive capabilities will be triggered by these BA resources, thereby creating marketing value.

Thus, conceptual arguments from prior literature suggest that absorptive capacity mediates the relationship between a healthcare organization's BA capability and decision-marking effectiveness. High levels of BA capability could enable healthcare organizations to support their decision making. Improved absorptive capacity provides an opportunity for them to speed up their decision making processes, enhance the quality of decision making, and deepen their understanding of their patients' needs. In contrast, without it they are less likely to achieve superior decision-making effectiveness. We therefore propose indirect impacts of BA in healthcare on decision-making effectiveness through the mediating role of absorptive capacity, expressed by the following hypotheses:

Hypothesis 5a (H5a): Absorptive capacity mediates the impact of effective use of data aggregation tools on decision-making effectiveness in health care.

Hypothesis 5b (H5b): Absorptive capacity mediates the impact of effective use of data analysis tools on decision-making effectiveness in health care.

Hypothesis 5c (H5c): Absorptive capacity mediates the impact of effective use of data interpretation tools on decision-making effectiveness in health care.

Research Methodology

Sampling frame and data collection

This study employed a survey method to collect primary data from Taiwan's healthcare industry. The sample population consisted of Taiwan's hospitals from the most recently available list of hospitals published by the Joint Commission of Taiwan (JCT). The qualifying hospitals should have experience of BA investment for the management and development of healthcare services. We posited that larger hospitals would be more likely to perform BA activities, so to be included in our study, a hospital had to be classified as either a medical center, regional hospital or district hospital and have at least 100 in-patient beds. Local clinics and psychiatric hospitals were excluded because they are generally too small to invest in BA. In all, 424 hospitals satisfied all the above criteria and were included in the survey.

This study focuses on whether healthcare organizations' decision making effectiveness can be improved by the use of BA systems. Thus, C-suite business executives, IT managers or senior IT staffs who were actively involved in BA activities were the subjects in this survey. We mailed one questionnaire to each hospital's primary contact, with a follow-up reminder two weeks later to non-respondents; in total, 424 questionnaires were sent to potential participants. Of the 155 responses received, three were incomplete, giving a 35.84% response rate with 152 valid data points. Of these respondents, 26.97% (n=41) were from C-suite business executives, including CEO and CIO, 47.37% (n=72) were IT managers and 25.66% (n=39) were senior IT staffs. With respect to hospital size, 76.32 % (n=116) of the participating hospitals had at least 200 employees. We recognized the difficulty and importance of finding respondents who can provide insights into various factors and so built in a selection filter by asking the participants to self-check against their level of experience regarding BA before taking the survey. The responses revealed that 78.94 % (n=120) of the participants had been working on BA projects for at least five years, 12.50% of the participants (n=19) had been working on BA projects for at least three years, and 8.56% of the participants (n=13) had at least one year BA experience. Since the primary focus of the present study is at the organizational level, the respondents' abundant experience in this area should provide some valuable insights.

Measurement

We developed a series of multi-item measures by either adopting scales that had been previously validated from the existing literature and modifying them appropriately to fit the context or by developing new scales where there was no existing validated scale. All the survey questions were translated into Chinese by one of the authors, after which two Chinese researchers double-checked the translations to ensure their accuracy. Appendix A lists the measurement items used. Responses to all the multi-item measures were captured using seven-point Likert-type scales.

Decision-making effectiveness: The measurement of this construct was based on reports in the relevant literature, suitably adapted to the context of health care (Cao et al., 2015, LaValle et al. 2011; Wixom et al., 2013). The speed with which a decision is reached is a key component of decision-making effectiveness expected from BA (Wixom et al., 2013), while understanding customers refers to the extent to which organizations understand their customers (Cao et al., 2015; LaValle et al., 2011). The quality of decision making was included based on Sanders and Courtney's (1985) suggestions. The resulting 3-item scale was used to capture responses by asking about whether the decision-making effectiveness can be satisfied with the aid of BA, with responses ranging from 1 = completely dissatisfied through 7 = completely satisfied.

Business analytics capabilities: As BA is still in its infancy in the IS field, there are no validated measurement items for BA capability, so to develop and validate an instrument for BA capability, we incorporated scale development procedures and recommendations from Lewis, Templeton and Byrd (2005) and Mackenzie, Podsakoff and Podsakoff (2011) as our guidelines. First, we selected appropriate constructs and underlying items by reviewing academic research, technical reports, and case studies. From a system functionality perspective, BA capabilities are operationalized into three dimensions: the effective use of data aggregation tools, the effective use of data analysis tools, and the effective use of data interpretation tools. These initial items aim to assess the extent to which each BA tool is used effectively in healthcare services. Next, content validity was verified and achieved through a pre-test. A small panel of three CIOs who work for healthcare organizations, five MIS researchers, and seven doctoral students in the MIS program were recruited as our content evaluation panel to review our instrument in terms of format, content, understandability, terminology, and ease and speed of completion. This panel was asked to act as judges by sorting items into groups and then critiquing the proposed items. We also asked the judges to identify specific items that should be added or deleted from the instrument, and to provide suggestions for improvement generally. Seven items were modified in accordance with their suggestions. A seven-point Likert-type scale was used for all the BA capability dimensions to capture responses by asking “please rate the effectiveness by which your organization uses the following BA tools in healthcare services”, ranging from 1= poorly developed to 7 = well developed.

Absorptive capacity: The measurement of this construct was adopted from Pavlou and El Sawy (2010), and modified to fit the context of health care. A 4-item scale was used to rate the effectiveness by which an organization can acquire, assimilate, transform, and exploit knowledge with the aid of BA. A seven-point Likert-type scale was again used to capture the responses, ranging from 1= strongly disagree to 7 = strongly agree.

Non-response bias and common method bias

Non-response bias. This aspect was assessed by comparing the early (those who responded to the first mailing) and late respondents (those who responded after the reminder), in terms of the number of employees using t-tests. The results showed no statistically significant difference between these two groups, indicating that non-response bias did not present a problem for this study.

Common method bias. To reduce common method bias, Podsakoff et al. (2003) suggest the use of specific procedures during both the design and data collection processes. Following these guidelines, we protected respondent-researcher anonymity, provided clear directions to the best of our ability, and proximally separated independent and dependent variables (Podsakoff et al., 2003). We then tested for bias statistically. First, Harman's one factor test (Brewer et al., 1970) was used to determine whether common method bias would pose a threat to the validity of this study's results. The results showed that five factors emerged with eigenvalues greater than 1. Of these, the first component accounted for 31.41% of the total variance and the unrotated factor solution indicated that no factor accounted for 50% or more of the variance. Second, following a procedure suggested by Pavlou et al. (2007), we compared correlations among the constructs. The results revealed no constructs with correlations over 0.7, whereas evidence of common method bias ought to have shown considerably higher correlations ($r>.90$). Consequently, these tests suggest that that common method bias is unlikely to pose a significant threat to the validity of this study.

Data Analysis and Results

Given our research model and objectives, structural equation modeling (SEM) was used to conduct data analysis. Three reasons drove this choice. First, SEM can examine proposed causal paths among constructs (Gefen et al., 2011). Second, the model does not include second-order formative constructs. Each indicator was modeled in a reflective manner. Third, our mediating variable, absorptive capacity was measured using multiple items which have to model the measurement error. Thus, SEM is more appropriate than PLS. We analyzed the data using IBM Amos 22.

Descriptive statistics and reliability and validity of scale

Table 2 presents the means, standard deviations, Cronbach's alphas, average variance extracted (AVE), Composite reliability, and construct correlations. The Cronbach's alphas (ranging from 0.80 to 0.91) indicate a satisfactory degree of internal consistency and reliability for the measures (Bollen & Lennox, 1991), with all values well above .70 (Nunnally & Bernstein, 1994). Construct reliability was assessed based on the composite construct reliabilities (CR) (Hair et al., 2010, p. 687). As shown in Table 2, the CRs ranged from 0.93 and 0.98, well over the commonly accepted cutoff value of .70 (Hair et al., 2010), thus demonstrating the adequate reliability of the measures.

Table 2. Descriptive Statistics and Correlations

Variable	Mean	S.D.	α	CR	1	2	3	4	5
Effective use of data aggregation	4.40	1.42	0.91	0.92	0.78				
Effective use of data analysis	4.65	1.33	0.84	0.85	0.05	0.59			
Effective use of data interpretation	3.97	1.20	0.91	0.91	0.19*	0.05	0.78		
Absorptive capacity	3.66	1.10	0.85	0.86	0.21**	0.19*	0.50**	0.60	

Decision-making effectiveness	4.32	1.14	0.80	0.80	0.11	0.17*	0.47**	0.47**	0.57

Note: N=152; AVEs on diagonal
CR: Composite reliability; *p<0.05, **p<0.01, ***p<0.001

Discriminant validity was first assessed by examining the construct correlations. Although there are no firm rules, inter-construct correlations below |.7| are generally considered to provide evidence of measure distinctness, and thus discriminant validity. None of the construct correlations were greater than .7, which demonstrates discriminant validity (see Table 3). Another way to examine discriminant validity is to compare the AVE to the squared inter-construct correlation. When the AVE is larger than the corresponding squared inter-construct correlation estimates, this suggests that the indicators have more in common with the construct they are associated with than they do with other constructs, which again provides evidence of discriminant validity. The data shown in Table 3 suggests the adequate divergent validity of the measures.

Exploratory factor analysis

For the measurement property evaluation, exploratory factor analysis (EFA) was conducted to explore the factor structure. Before performing the factor analysis, we verified that the data were appropriate for factor analysis using the Kaiser–Meyer–Olkin (KMO) test and the Bartlett sphericity test. The results of both tests indicated that a factor analysis would be useful given our data (KMO=0.815; $\chi 2$ = 1502.457; df =136 p < .000). The initial factor analysis using principal components analysis extracted four factors that were evident on the scree plot, all with an eigenvalue greater than one. Factor loadings for the effective use of the data aggregation block ranged from 0.894 to 0.928, the effective use of the data analysis block ranged from 0.675 to 0.865, the effective use of data interpretation from 0.819 to 0.910, the absorptive capacity block ranged from 0.686 to 0.850, and the decision-making effectiveness block ranged from 0.673 to 0.857. Overall, the results for EFA achieved standard factor loadings of 0.5 as the cut-off significance, confirming that individual factors can indeed be identified in a given block of dimensions.

Measurement model

A measurement model was then analyzed to assess the measurement quality of the constructs using a confirmatory factor analysis (CFA). The measurement model consisted of five factors. The loading ranges for these five factors were as follow: the effective use of data aggregation, 0.816 to 0.932; the effective use of data analysis, 0.574 to 0.825; the effective use of data interpretation, 0.830 to 0.945; absorptive capacity, 0.674 to 0.845; and decision-making effectiveness, 0.700 to 0.793. The model chi-square was not statistically significant (χ^2 (109) = 143.117, $p > .05$), which indicates that the exact fit hypothesis should be accepted. The comparative fit index (CFI) was 0.976, which exceeds the cutoff value of 0.80, and the standardized root mean square residual (SRMR) was 0.0557. The root mean square error of the approximation (RMSEA) was 0.046, which is less than 0.08. Thus, we concluded that our data adequately fit the measurement model.

Mediating effect testing

We followed the procedures proposed by Tang et al. (2014) to test the mediating effects of absorptive capacity. We compared five alternative models in terms of their fit statistics and path coefficients. The fit statistics for the models are shown in Table 3. First, the proposed model (Model A) in which the path coefficients among the five latent variables were freely estimated was tested. The absolute value of and CFI was well above 0.95 and SRMR and RMSEA were both less than .08 for Model A. Then, a series of alternative structural models were tested against each other. After comparing Model B, in which all path coefficients among the five latent variables were constrained to zero, to the direct model (Model C), in which all path coefficients to and from absorptive capacity were constrained to zero, we found that Model C produced a significantly better fit to the data compared to Model B. In Model C, we examined the impact of BA captivity alone on decision-making effectiveness. The results revealed that the path coefficient was significant from the effective use of data interpretation tools to decision-making effectiveness, but insignificant from the effective use data analysis and aggregation tools to decision-making effectiveness. Next, Model D, in which all path coefficients from the three forms of BA capabilities were constrained to zero, was also compared to the baseline model (Model B). Hypothesis 1 was supported because Model D produced a significantly better fit to the data compared to Model B and the path coefficient from absorptive capacity to decision-making effectiveness was significant.

The full mediation model (Model E), in which all path coefficients from the three forms of BA capabilities to decision-making effectiveness were constrained to zero, was then compared to Model C and Model D. The results showed that Model E produced a significantly better fit to the data compared to either Model C or Model D, indicating that the effective use of data analysis and interpretation tools positively affects absorptive capacity. Thus, Hypothesis 3 and Hypothesis 4 were supported, but Hypothesis 2 was not supported. Finally, the proposed model (Model A) was compared to Model E; the results showed that Model A fit the data slightly better than Model E. We thus concluded that our proposed model (Model A) provided the most parsimonious fit to the data.

The paths and parameter estimates for the proposed model (Model A) are shown in Figure 2, which indicates that absorptive capacity had the greatest association with decision-making effectiveness and the path coefficients from business capabilities to absorptive capacity became insignificant after adding a mediator (in this case, absorptive capacity). While it mediated the relationships between the effective use of data analysis tools and both the effective use of data interpretation tools and the decision-making effectiveness, it failed to mediate the relationship between the effective use of data aggregation tools and decision-making effectiveness because the path coefficient between effective use of data aggregation tools and absorptive capacity was not significant. As the direct effects of the effective use of data analysis tools on decision-making effectiveness was not significant, this indicates that absorptive capacity fully mediated the relationship between them. However, as the direct effects of effective use of data interpretation tools on decision-making effectiveness was significant, the absorptive capacity only partially mediated the relationship between them.

To further confirm the mediating role of absorptive capacity, a bootstrapping analysis was used to assess the significance of each indirect effect. As recommended by Cheung and Lau (2008), we set the number of bootstrap samples as 1,000. The results showed that the two-sided bias-corrected bootstrap confidence interval for the indirect effect of data interpretation tools on decision-making effectiveness through absorptive capacity was [0.269, 0.511], that for the indirect effect of data aggregation tools on decision-making effectiveness was [-0.016, 0.0149] and for the indirect effect of data analysis tools on decision-making effectiveness it was [0.018, 0.314]. Thus, the indirect (mediated) effects of data analysis and interpretation tools on decision-making effectiveness were both significant, whereas the indirect effect of data aggregation tools on the decision-making effectiveness was not significant, consistent with the aforementioned results. Thus, Hypotheses 5b and 5c were supported, but Hypothesis 5a was not supported.

Table 3. Model Fit Summary and Nested Model Comparisons

Model	Chi-square	df	p-value	Δ χ2	CFI	SRMR	RMSEA (90C.I.)
A	150.248	112	.009	-	0.973	0.0785	0.048 (0.025, 0.066)
B	245.963	119	.000	95.715	0.911	0.1962	0.840 (0.069, 0.099)
C	209.907	116	.000	59.659	0.935	0.1719	0.073 (0.057, 0.089)
D	210.907	118	.000	60.659	0.935	0.1730	0.072 (0.056, 0.088)
E	162.321	115	.002	12.073	0.967	0.0880	0.052 (0.032, 0.070)

Notes: SRMR = standard root mean square residual; CFI = comparative fit index; RMSEA = root mean square error of approximation.
The proposed model served as the baseline for chi-square difference testing
Model A: the proposed model, no path coefficients among the five latent variables were constrained to zero.
Model B: all path coefficients among the five latent variables were constrained to zero.
Model C: all path coefficients to and from absorptive capacity were constrained to zero.
Model D: all path coefficients from BA capabilities were constrained to zero.
Model E: all path coefficients from the BA capabilities to decision-making effectiveness were constrained to zero.

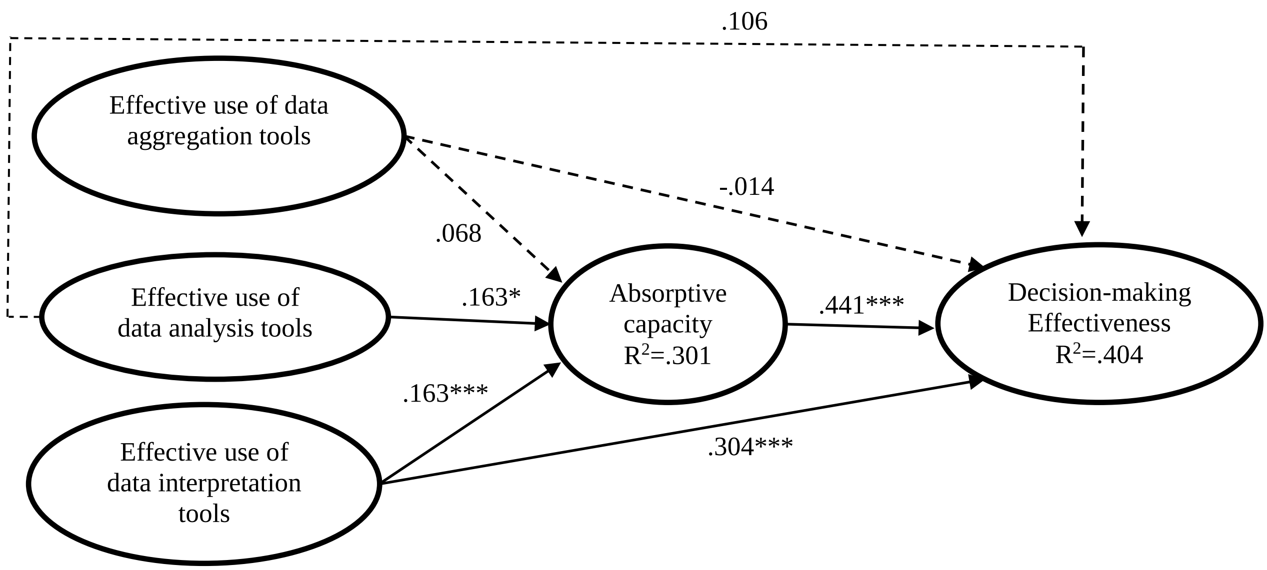


Figure 2. Path diagram and standardized estimates
Note: Summary of standardized path coefficients for the hypothesized model with the full sample (N = 152). Solid lines represent significant coefficients, and dotted lines represent non-significant coefficients, * p < .05; ** p < .01; *** p < .001.

Discussion

The main objective of this research was to advance our understanding of the way BA enables healthcare units to enjoy better decision-making effectiveness through the absorption of the new knowledge provided by the BA systems. By applying the RBV and the dynamic capability view, this study proposes a conceptual model in which BA capabilities, as lower-order capabilities, exert influence on decision making effectiveness through a higher-order capability, namely absorptive capacity. The empirical evidence collected for this study supports five key findings.

First, the results strongly support the claim that healthcare organizations' BA capabilities – both the effective use of data analysis and interpretation tools – can help improve its absorptive capacity. This finding is consistent with prior studies that emphasized the notion that the amplifying role of lower-order IT or operational capabilities can be developed to improve organizational capabilities (e.g., Liu et al., 2013; Pavlou & El Sawy, 2006; 2010). Second, with respect to indirect effect, the effective use of interpretation tools in healthcare units indirectly influences decision-making effectiveness, an impact that is mediated by absorptive capacity. This means that hospitals are likely to create valuable knowledge to make sound clinical decisions as they utilize visual dashboards and metrics effectively (Jardine et al., 2014; Spruit et al., 2014). Third, consistent with the dynamic capabilities view which contends the effective of IT capability on competitive advantage are fully mediated by dynamic capability (Pavlou & El Sawy, 2006; 2010), the mediating effect test indicates the full mediation of absorptive capacity on the relationship between the effective use of data analysis tools and decision making effective. Fourth, as we expected, the findings have highlighted the critical role of absorptive capacity in achieving decision making effectiveness in health care. Finally, the results of this study do not support the hypothesis on the association of the effective use of data aggregation tools and absorptive capacity as well as decision making effectiveness. A possible explanation is that the majority of respondents (74.34%) were from the top-level management (i.e., CEO, CIO) and middle-level management (i.e., IT managers). They are not responsible for aggregating and dealing with patient data in back-end systems. Although data aggregation is a precursor requirement to data analysis and interpretation and remains important, many care providers are suffering from data aggregation-related issues such as the lack of data standards and data integration, data overload issues, and barriers to the collection of high-quality data (Ashrafi et al., 2014; Shah & Patak, 2014; Ward et al., 2014) Thus, healthcare managers have to be aware of the importance of data aggregation tools as implementing BA systems. Based on these findings, we can offer some useful insights regarding the theoretical and managerial implications of these findings.

Theoretical contributions and implications

A compelling question in the IS literature, particularly related to the business value of IT research, is how BA can be used to obtain business value since the implementation of BA systems is still at an early stage. This study makes two main contributions towards this question. First, the conceptualization and operationalization of the construct of BA capability has contributed to the development of a deeper understanding of BA. Few previous researchers have sought to measure BA capability by modeling it as a one-dimension construct, instead choosing to focus solely on examinations of the data analysis process. However, such approaches may unintentionally overlook other important facets of BA capability, such as its ability to visualize data. The business value of IT research has tended to focus on a nominal view of the IT artifact that generally advocates the benefits of IT use, but without mentioning any specific technology

(Orlikowski & Iacono, 2001). Going beyond this view, the proposed construct draws on a broader view of IT functionality that allows us to capture BA more fully by reviewing its functionalities and how it is actually implemented in real-world healthcare units to conceptualize the BA capability. This conceptualization is the first step towards building a much needed body of knowledge on the business value of BA and provides researchers with a useful lens through which to examine the effectiveness of BA systems in supporting various organizational practices.

Second, a theoretical basis for the relationship between BA capability and decision-making effectiveness was elucidated here by adopting an absorptive capacity perspective that is rooted in RBV and dynamic capability veiw. Our results demonstrate how knowledge absorption matters when applying BA to the decision making process by examining its mediation role. This implies that BA per se does not create business value, but that an organization’s ability to identify, extract, transform, and utilize knowledge can transform the impact of BA use into actual organizational performance, speeding up the organization’s decision making, improving the quality of the decisions made, and helping it to develop a better understanding of its customers. Specifically, our finding suggests that the effective use of data analysis and aggregation tools has no business value, thus affirming the commonly held view of the IT productivity paradox in the healthcare context (Jones et al., 2012). However, the mediating role of absorptive capacity not only provides a mechanism by which BA can contribute to decision making practices, but also offers a new solution to the puzzle of the IT productivity paradox in healthcare settings.

Implications for practice

For project leaders who are responsible for implementing BA systems, this study provides a set of interesting insights that may affect the scope of their current projects. First, even if IT vendors have enthusiastically advocated the potential benefits of BA when used for various business practices, BA implementation requires organizational changes if it is to be effective. In addition to the technological issues of BA, managers must also turn their attention to integrating knowledge management into BA initiatives, focusing particularly on ways to harness BA-generated knowledge. Healthcare organizations must constantly seek and disseminate new knowledge to respond to industry regulations and market needs. According to our results, healthcare organizations' ability to obtain and apply knowledge becomes critical, since knowledge generated from the use of BA per se cannot generate value. Thus, a strong knowledge management protocol could add tremendous value during BA implementation.

Second, our results show that data interpretation is a crucial capability that directly impacts decision-making effectiveness. Although BA can create convenient summarized reports or charts, the key to making these reports meaningfully is to equip managers and employees with relevant professional skills. Incorrect interpretation of the reports generated could lead to serious errors of judgment and questionable decisions. Managers should provide suitable analytical training courses for the employees who will play a critical support role in the new information-rich work environment if organizations are to make best use of their new opportunities to transfer data into knowledge.

Conclusion

Notwithstanding the above-mentioned contributions and implications, our study is inevitably subject to some limitations. First, different industries have different needs, goals and expectations when implementing BA solutions. We targeted healthcare industries for this study, so the generalizability of the results is limited, because data were only collected from a limited sample consisting of large hospitals in Taiwan. Thus, our findings are not applicable to healthcare industries in other countries. Second, the sample size used for validating the BA capability scale was relatively small, although the representativeness of our sample may overcome the sample size issue to some extent. More than 70% of the participants in this study served as senior IT executives and were thus able to provide strategic overviews of the BA implementation in their healthcare organizations. Meanwhile, by carefully taking various steps for scale development, we tried to minimize the potential bias. Third, in order to make stronger conclusions from research, further empirical research should validate the scales of business analytics capability by utilizing larger samples. Finally, given its exclusive focus on BA capability, our study does not consider other possible factors contributing to BA success.

In response to the limitations of the current study, we offer some suggestions for future research. A more comprehensive study is now needed that examines other factors that may serve as enablers or moderating or mediating roles for this path. As the business value of IT research suggests, several human IT resource (e.g., the analytical personnel's skills), other organizational capability factors (e.g., dynamic capability, improvisational capabilities), organizational complementary resources (data government, synergy, and culture), and environmental factors (market and environmental turbulent) could all play a role and should thus be examined. Also, rather than examining the aforementioned factors with singular causation and linear associations, future studies could seek to capture the complex interactions of the interdependencies among BA capabilities and other organizational elements, and examine how different configurations create improved business value.

In conclusion, our primary research objective was to unravel the relationships among BA capability, absorptive capacity and decision making effectiveness. With our focus on the role of absorptive capacity, we found that BA systems may indeed reveal new opportunities for transforming decision making process. Consequently, the findings of this study provide interesting new insights into knowledge management, contributing to the BA literature by proposing a BA-enabled decision making effectiveness model that takes into account the effect of absorptive capacity.

Appendix A: Measurement Items

Effective use of data aggregation tools (Newly developed)

Please rate the effectiveness by which your organization uses the following business analytics tools in the healthcare services.

1. Collect data from external healthcare sources and from various health systems throughout your organization.
2. Make patient records consistent, visible and easily accessible for further analysis.
3. Store patient data into appropriate databases.

Effective use of data analysis tools (Newly developed)

1. Identify important business insights and trends to improve healthcare services.
2. Predict patterns of care in response to patient needs.
3. Analyze data in near-real or real time that allows responses to unexpected clinical events.
4. Analyze social media data to understand current trends from a large population.

Effective use of data interpretation tools (Newly developed)

1. Provide systemic and comprehensive reporting to help recognize feasible opportunities for care improvement.
2. Support data visualization that enables users to easily interpret results.
3. Provide near-real or real time information on health care operations and services within healthcare facilities and across health care systems.

Absorptive capacity (Pavlou & El Sawy, 2010)

Please rate the effectiveness by which your organization can acquire, assimilate, transform, and exploit knowledge with the aid of business analytics.

1. We have effective routines to identify value, and import new information and knowledge.
2. We have adequate routines to assimilate new information and knowledge.
3. We are effective in transforming existing information into new knowledge.
4. We are effective in utilizing knowledge into new services.

Decision-making Effectiveness (Cao et al., 2015; Sanders & Courtney, 1985; Wixom et al., 2013)

1. As a result of business analytics systems, the quality of decisions has improved.
2. As a result of business analytics systems, the speed at which we analyze decisions has increased.
3. As a result of business analytics systems, we have an increased understanding of our customers.

References

Ashrafi, N., Kelleher, L. & Kuilboer, J. P. (2014). The impact of business intelligence on healthcare delivery in the USA. *Interdisciplinary Journal of Information, Knowledge, and Management*, 9, 117-130.

Bardhan, I., Oh, J. H., Zheng, Z., & Kirksey, K. (2014). Predictive analytics for readmission of patients with congestive heart failure. *Information Systems Research*, 26(1), 19-39.

Barjis, J., Kolfschoten, G., & Maritz, J. (2013). A sustainable and affordable support system for rural healthcare delivery. *Decision Support Systems*, 56, 223-233.

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, 17(1), 99-120.

Barney, J. B. (2001). Resource-based theories of competitive advantage: A ten-year retrospective on the resource-based view. *Journal of Management*, 27(6), 643-650.

Bates, D. W., Saria, S., Ohno-Machado, L., Shah, A., & Escobar, G. (2014). Big data in health care: using analytics to identify and manage high-risk and high-cost patients. *Health Affairs*, 33(7), 1123-1131.

Belle, A., Thiagarajan, R., Soroushmehr, S. M., Navidi, F., Beard, D. A., & Najarian, K. (2015). Big data analytics in healthcare. *BioMed Research International*, 2015, 1-16.

Bharadwaj, A. S. (2000). A resource-based perspective on information technology capability and firm performance: an empirical investigation. *MIS Quarterly*, 24(1), 169-196.

Bollen, K., & Lennox, R. (1991). Conventional wisdom on measurement: A structural equation perspective. *Psychological bulletin*, 110(2), 305-314.

Brewer, M. B., Campbell, D. T., & Crano, W. D. (1970). Testing a single-factor model as an alternative to the misuse of partial correlations in hypothesis-testing research. *Sociometry*, 33(1), 1-11.

Bromiley, P., & Rau, D. (2014). Towards a practice-based view of strategy. *Strategic Management Journal*, 35(8), 1249-1256.

Brooks, P., El-Gayar, O., & Sarnikar, S. (2015). A framework for developing a domain specific business intelligence maturity model: Application to healthcare. *International Journal of Information Management*, 35(3), 337-345.

Cao, G., Duan, Y., & Li, G. (2015). Linking Business Analytics to Decision Making Effectiveness: A Path Model Analysis. *IEEE Transactions on Engineering Management*, 62(3), 384-395.

Chae, B., Olson, D., & Sheu, C. (2014). The impact of supply chain analytics on operational performance: A resource-based view. *International Journal of Production Research*, 52(16), 4695-4710.

Chasalow, L. C., & Baker, E. W. (2015). Factors contributing to business intelligence success: The impact of dynamic capabilities. In *Proceeding of Twenty-first Americas Conference on Information Systems*, Puerto Rico, USA.

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

Cheung, G. W., & Lau, R. S. (2007). Testing mediation and suppression effects of latent variables: Bootstrapping with structural equation models. *Organizational Research Methods*, 11(2), 296-325.

Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly*, 35(1), 128-152.

Cortada, J.W., Gordon, D., & Lenihan, B. (2012). *The Value of Analytics in Healthcare: From Insights to Outcomes*. Somers, NY: IBM Global Business Services.

Davenport, T. H., & Harris, J. G. (2007). *Competing on Analytics: The New Science of Winning*. Harvard Business Press.

Delen, D. (2014). *Real-World Data Mining: Applied Business Analytics and Decision Making*. FT Press.

DeLone, W. H., & McLean, E. R. (1992). Information systems success: the quest for the dependent variable. *Information Systems Research*, 3(1), 60-95.

Devaraj, S., & Kohli, R. (2003). Performance impacts of information technology: Is actual usage the missing link?. *Management Science*, 49(3), 273-289.

El Sawy, O. A., Malhotra, A., Park, Y., & Pavlou, P. A. (2010). Research commentary-seeking the configurations of digital Ecodynamics: It takes three to tango. *Information Systems Research*, 21(4), 835-848.

Elbashir, M. Z., Collier, P. A., & Sutton, S. G. (2011). The role of organizational absorptive capacity in strategic use of business intelligence to support integrated management control systems. *The Accounting Review*, 86(1), 155-184.

Erevelles, S., Fukawa, N., & Swayne, L. (2016). Big data consumer analytics and the transformation of marketing. *Journal of Business Resear*ch, 69(2), 897-904.

Fan, W., & Gordon, M. D. (2014). The power of social media analytics. *Communications of the ACM*, 57(6), 74-81.

Fihn, S. D., Francis, J., Clancy, C., Nielson, C., Nelson, K., Rumsfeld, J., ... & Graham, G. L. (2014). Insights from advanced analytics at the Veterans Health Administration. *Health Affairs*, 33(7), 1203-1211.

Flatten, T. C., Engelen, A., Zahra, S. A., & Brettel, M. (2011). A measure of absorptive capacity: Scale development and validation. *European Management Journal*, 29(2), 98-116.

Foshay, N., & Kuziemsky, C. (2014). Towards an implementation framework for business intelligence in healthcare. *International Journal of Information Management*, 34(1), 20-27

Francalanci, C., & Morabito, V. (2008). IS integration and business performance: The mediation effect of organizational absorptive capacity in SMEs. *Journal of Information Technology*, 23(4), 297-312.

Galbraith, J. R. (1974). Organization design: An information processing view. *Interfaces*, 4(3), 28-36.

Gefen, D., Rigdon, E. E., & Straub, D. (2011). An update and extension to SEM guidelines for administrative and social science research. *MIS Quarterly*, 35(2), iii-xiv.

Ghosh, B., & Scott, J. E. (2011). Antecedents and catalysts for developing a healthcare analytic capability. *Communications of the Association for Information Systems*, 29(1), 395-410.

Grewal, R., & Slotegraaf, R. J. (2007). Embeddedness of organizational capabilities. *Decision Sciences*, 38(3), 451-488.

Groves, P., Kayyali, B., Knott, D., & Kuiken, S.V. (2013). *The "Big Data" Revolution in Healthcare: Accelerating Value and Innovation*. McKinsey & Company.

Hair Jr., J. F., Black, W., Babin, B., & Anderson, R. (2010). *Multivariate Data Analysis (7th ed.)*. Pearson Education Inc.

Halamka, J. D. (2014). Early experiences with big data at an academic medical center. *Health Affairs*, 33(7), 1132-1138.

Hu, H., Wen, Y., Chua, T. S., & Li, X. (2014). Toward scalable systems for big data analytics: a technology tutorial. *Access, IEEE*, 2, 652-687.

Işık, Ö., Jones, M. C., & Sidorova, A. (2013). Business intelligence success: The roles of BI capabilities and decision environments. *Information & Management*, 50(1), 13-23.

Jardine, A., Mullan, N., Gudes, O., Cosford, J., Moncrieff, S., West, G., ... & Someford, P. (2014). Web-based geo-visualisation of spatial information to support evidence-based health policy: A case study of the development process of 'HealthTracks'. *Health Information Management Journal*, 43(2), 7-16.

Jones, S. S., Heaton, P. S., Rudin, R. S., & Schneider, E. C. (2012). Unraveling the IT productivity paradox - lessons for health care. *New England Journal of Medicine*, 366(24), 2243-2245.

Joshi, K. D., Chi, L., Datta, A., & Han, S. (2010). Changing the competitive landscape: Continuous innovation through IT-enabled knowledge capabilities. *Information Systems Research*, 21(3), 472-495.

Karimi, J., Somers, T. M., & Bhattacherjee, A. (2007). The role of information systems resources in ERP capability building and business process outcomes. *Journal of Management Information Systems*, 24(2), 221-260.

Knabke, T., & Olbrich, S. (2015). Exploring the future shape of business intelligence: mapping dynamic capabilities of information systems to business intelligence agility. In *Proceeding* *of The Twenty-First Americas Conference on Information Systems (AMCIS 2015)*, Puerto Rico.

Kowalczyk, D. W. I. M., & Buxmann, P. (2014). Big data and information processing in organizational decision processes. *Business & Information Systems Engineering*, 6(5), 267-278.

Kwon, O., Lee, N., & Shin, B. (2014). Data quality management, data usage experience and acquisition intention of big data analytics. *International Journal of Information Management*, 34(3), 387-394.

LaValle, S., Lesser, E., Shockley, R., Hopkins, M. S., & Kruschwitz, N. (2011). Big data, analytics and the path from insights to value. *MIT Sloan Management Review*, 52(2), 21-31.

Lewis, B. R., Templeton, G. F., & Byrd, T. A. (2005). A methodology for construct development in MIS research. *European Journal of Information Systems*, 14(4), 388-400.

Lichtenthaler, U. (2009). Absorptive capacity, environmental turbulence, and the complementarity of organizational learning processes. *Academy of Management Journal*, 52(4), 822-846.

Lin, Y., Brown, R. A., Yang, H. J., Li, S., Lu, H., & Chen, H. (2011). Data mining large-scale electronic health records for clinical support. *IEEE Intelligent Systems*, 26(5), 87-90.

Lin, Y., Wang, Y., & Kung, L. (2015). Influences of cross-functional collaboration and knowledge creation on technology commercialization: evidence from high-tech industries. *Industrial Marketing Management*, 49, 128-138.

Liu, H., Ke, W., Wei, K. K., & Hua, Z. (2013). The impact of IT capabilities on firm performance: The mediating roles of absorptive capacity and supply chain agility. *Decision Support Systems*, 54(3), 1452-1462.

MacKenzie, S. B., Podsakoff, P. M., & Podsakoff, N. P. (2011). Construct measurement and validation procedures in MIS and behavioral research: Integrating new and existing techniques. *MIS Quarterly*, 35(2), 293-334.

Malhotra, A., Gosain, S., & Sawy, O. A. E. (2005). Absorptive capacity configurations in supply chains: gearing for partner-enabled market knowledge creation. *MIS Quarterly*, 29(1), 145-187.

McAfee, A., & Brynjolfsson, E. (2012). Big data. the management revolution. *Harvard Business Review*, 90(10), 59-68.

Meador, C. L., Guyote, M. J., & Keen, P. G. (1984). Setting priorities for DSS development. *MIS Quarterly*, 8(2), 117-129.

Melville, N., Kraemer, K., & Gurbaxani, V. (2004). Review: Information technology and organizational performance: An integrative model of IT business value. *MIS Quarterly*, 28(2), 283-322.

Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric Theory*, New York: McGraw-Hill.

Orlikowski, W. J., & Iacono, C. S. (2001). Research commentary: Desperately seeking the "IT" in IT research—A call to theorizing the IT artifact. *Information Systems Research*, 12(2), 121-134.

Pavlou, P. A., & El Sawy, O. A. (2006). From IT leveraging competence to competitive advantage in turbulent environments: The case of new product development. *Information Systems Research*, 17(3), 198-227.

Pavlou, P. A., & El Sawy, O. A. (2010). The "third hand": IT-enabled competitive advantage in turbulence through improvisational capabilities. *Information Systems Research*, 21(3), 443-471.

Pavlou, P. A., Liang, H., & Xue, Y. (2007). Understanding and mitigating uncertainty in online environments: a principal-agent perspective. *MIS Quarterly*, 31(1), 105-136.

Phillips-Wren, G., Iyer, L. S., Kulkarni, U., & Ariyachandra, T. (2015). Business analytics in the context of big data: a roadmap for research. *Communications of the Association for Information Systems,* 37, 448-472.

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: a critical review of the literature and recommended remedies. *Journal of Applied Psychology*, 88(5), 879-903.

Popovič, A., Hackney, R., Coelho, P. S., & Jaklič, J. (2012). Towards business intelligence systems success: Effects of maturity and culture on analytical decision making. *Decision Support Systems*, 54(1), 729-739.

Power, D. J. (2008). *Decision Support Systems: A Historical Overview*. in Handbook on Decision Support Systems, Springer, Berlin Heidelberg.

Raghupathi, W., & Raghupathi, V. (2014). Big data analytics in healthcare: promise and potential. *Health Information Science and Systems*, 2(1), 1-10.

Riabacke, M., Danielson, M., & Ekenberg, L. (2012). State-of-the-art prescriptive criteria weight elicitation. *Advances in Decision Sciences*, 2012, 1-24.

Roberts, N., Galluch, P. S., Dinger, M., & Grover, V. (2012). Absorptive capacity and information systems research: Review, synthesis, and directions for future research. *MIS Quarterly*, 36(2), 625-648.

Roski, J., Bo-Linn, G. W., & Andrews, T. A. (2014). Creating value in health care through big data: opportunities and policy implications. *Health Affairs*, 33(7), 1115-1122.

Sanders, G. L., & Courtney, J. F. (1985). A field study of organizational factors influencing DSS success. *MIS Quarterly*, 9(1), 77-93.

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

Schryen, G. (2013). Revisiting IS business value research: what we already know, what we still need to know, and how we can get there. *European Journal of Information Systems*, 22(2), 139-169.

Seddon, P. B., Constantinidis, D., & Dod, H. (2012). How does business analytics contribute to business value? In *Proceeding of the 33rd International Conference on Information Systems*, Orlando, Florida.

Shanks, G., & Bekmamedova, N. (2012). Achieving benefits with business analytics systems: An evolutionary process perspective. *Journal of Decision Systems*, 21(3), 231-244.

Sharma, R., & Yetton, P. (2003). The contingent effects of management support and task interdependence on successful information systems implementation. *MIS Quarterly*, 27(4), 533-556.

Sharma, R., Mithas, S., & Kankanhalli, A. (2014). Transforming decision-making processes: a research agenda for understanding the impact of business analytics on organisations. *European Journal of Information Systems*, 23(4), 433-441.

Song, M., Berends, H., Van der Bij, H., & Weggeman, M. (2007). The effect of IT and co-location on knowledge dissemination. *Journal of Product Innovation Management*, 24(1), 52-68.

Spruit, M., Vroon, R., & Batenburg, R. (2014). Towards healthcare business intelligence in long-term care: An explorative case study in the Netherlands. *Computers in Human Behavior*, 30, 698-707.

Srinivasan, U., & Arunasalam, B. (2013), Leveraging big data analytics to reduce healthcare costs. *IT Professional*, 15(6), 21-28.

Tamm, T., Seddon, P., & Shanks, G. (2013). Pathways to value from business analytics. In, Milan, Italy. *Proceeding of the Thirty Fourth International Conference on Information Systems*

Tang, S. W., Siu, O. L., & Cheung, F. (2014). A study of work–family enrichment among Chinese employees: the mediating role between work support and job satisfaction. *Applied Psychology*, 63(1), 130-150.

Trkman, P., McCormack, K., De Oliveira, M. P. V., & Ladeira, M. B. (2010). The impact of business analytics on supply chain performance. *Decision Support Systems*, 49(3), 318-327.

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

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

Wang, Y., Kung, L., Ting, C., & Byrd, T. A. (2015), Beyond a technical perspective: understanding big data capabilities in health care. In System Sciences (HICSS), 2015 48th Hawaii International Conference on (pp. 3044-3053). IEEE.

Ward, M. J., Marsolo, K. A., & Froehle, C. M. (2014). Applications of business analytics in healthcare. *Business Horizons*, 57(5), 571-582.

Watson, H. J. (2014), Tutorial: big data analytics: concepts, technologies, and applications. *Communications of the Association for Information Systems*, 34, 1247-1268.

Webster, J., & Watson, R. T. (2002). *Analyzing the past to prepare for the future: writing a literature review*. *MIS Quarterly*, 26(2), xiii-xxiii.

Wickramasinghe, N., & Schaffer, J. L. (2006). Creating knowledge-driven healthcare processes with the intelligence continuum. *International Journal of Electronic Healthcare*, 2(2), 164-174.

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

Zahra, S. A., & George, G. (2002). The net-enabled business innovation cycle and the evolution of dynamic capabilities. *Information Systems Research*, 13(2), 147-150.

Essay 3: Exploring Configurations for Maximizing Quality of Care from Big Data Analytics in Healthcare

Introduction

Over the past five years, big data analytics is increasingly being advocated as an important strategic information technology (IT) investment for healthcare organizations even though a typical big data project costs approximately $9.3 million for building and maintaining Hadoop systems in a 5-year period (Winter, Gilbert, & Davis, 2013). Many success stories in healthcare from key IT vendors reported that big data analytics has the potential to harvest data-driven insights, support evidence-based medicine, and improve quality of care at a lower cost (Gillon et al., 2014; Groves, Kayyali, Knott, & Kuiken, 2013; Schneeweiss, 2014; Raghupathi & Raghupathi, 2014; Ward et al., 2014), all of which are indicators for higher healthcare organization performances. Since big data analytics systems can be an expensive and risky undertaking (Watson, 2014), it is imperative to explore and present the value of big data analytics for healthcare managers to make their business cases. As any disruptive innovation, big data analytics' contribution to business value for healthcare still lacks a holistic view at this early stage.

A few studies develop big data analytics success models through the paradigmatic lenses of process and variance theories (e.g., Cao et al., 2015; Seddon, Constantinidis, & Dod, 2012; Tamm, Seddon, & Shanks, 2013; Wang, Kung, Wang, & Cegielski, 2014). From a process theories perspective, researchers explore the compelling pathways starting from analytics use capabilities, through insights and decisions, to organizational benefits over time (e.g., Seddon et al., 2012; Sharma, Mithas, & Kankanhalli, 2014). Variance theories, on the other hand, help identify critical success factors of big data analytics such as big data analytics infrastructure and functionalities (e.g., Cao et al., 2015; Trkman et al., 2010; Wang et al., 2014; Wixom et al., 2013), analytical people (Gao et al., 2015; Seddon et al., 2012; Tamm et al., 2013), data-driven decision-marking culture (Seddon et al., 2012) and data-driven environment (Cao et al., 2015) that lead to reshape organizational capabilities and generate economic value, Although these studies have explicitly explored the impact of big data analytics on facilitating decision making and enhancing organizational benefits, strong empirical evidence of how big data analytics contributes to business value is needed.

In this study, we seek to explain the role of big data analytics in healthcare organization performance from the theoretical perspectives that business value generation is a complex process (Bharadwaj, 2000; Melville et al., 2004; Nevo & Wade, 2010) that will be very difficult to portrait using regression-based methods. A systemic and simultaneous arrangement of multiple elements (Fichman, 2004; Fichman et al., 2014) interacting with each other provides a more holistic and more realistic view of such complex process.

We first conceptualize a multi-dimensional big data analytics capability construct based on resource-based view of IT (Bharadwaj, 2000; Santhanam & Hartono, 2003), which contends that a firm's unique IT capability can be constructed by the configurations of available tangible and intangible IT resources or the synergetic combination of non-valuable, rare, imperfectly imitable and non-substitutable (VRIN) resources. Big data analytics capabilities are shaped by a set of technological big data analytics resources (e.g., design principles and functionalities of big data analytics systems) and human big data analytics resources (e.g., analytical people). We first identified elements from the literature, resulted in a set consists of four elements of big data analytics capabilities - traceability, analytical capability, decision support capability, and predictive capability – and two elements of analytics personnel capabilities - technical skills, and business skills. Then we need to identify their interactions. This leads to our first research question:

(1) How do elements of big data analytics capabilities combine in different configurations to help create higher quality of care in health care?

Business value of IT literature suggests that IT alone does not unequivocally facilitate strategic advantage (El Sawy, Malhotra, Park, & Pavlou, 2010). The link between IT and business value is most likely not a direct path but rather a complex process when considering other complementary elements in the organization. Complementary organizational elements (e.g., culture, policies and rules, and organizational structure), and organizational capabilities in the business processes were noted as key elements in generating business value with IT (Melville et al., 2004; Nevo & Wade, 2010). ilities (Cao et al., 2015; Kung, Kung, Jones-Farmer, & Wang, 2015; Shanks & Bekmanedova, 2012; Seddon et al., 2012). Pertaining to big data analytics, literature has identified multiple organizational elements such as evidence-based decision making culture (e.g., Kiron et al., 2012; Kiron & Shockely, 2011; Popovič et al., 2012; Ross, Beath, & Quaadgras, 2013) and data governance (LaValle et al., 2011; Seddon et al., 2012; Wang et al., 2015) that are complementary, interdependent and together would shape business value. This leads to our second research question:

(2) How do other organizational elements (i.e., complementary resource and organizational capabilities) combine with big data analytics capabilities to achieve higher quality of care in health care?

Rather than examining the elements with linear associations, this study captures the complex interactions of the interdependencies among big data analytics capabilities and other organizational elements, and examines how different configurations cause improved business value in health care. In doing so, this research first contributes to theory by proposing a conceptual model with a holistic view that helps healthcare organizations scope their big data analytics initiatives. Secondly, based on empirical data, it identifies different configurations of conditions leading to higher business value in healthcare which extends and deepens the understanding of business value of big data analytics. Applying configurational theory, it allows for the presentation of complex interactions among the factors (elements) that go beyond simple linear additive or multiplicative effects. Configurations found provide evidences for how different relational aspects interact with each other to create organizational performance in healthcare in different situations. Thirdly, our findings provide useful guidance for practitioners with regard to the management and configuration of big data analytics.

The organization of this paper is as follows. This paper first reviews the current research focusing on developing the models for big data analytics success and then we describe the configuration view and discuss why it is better suited to examine the complexity of achieving business value with big data analytics. Then, we develop a configurational model for business value creation of big data analytics by defining potential big data analytics capabilities, analytical personnel capabilities, and other complementary elements in the health care context. Next, we describe the survey that was used to collect data and the results from fsQCA of the research model. The findings are discussed in the concluding sections.

Literature Review

Research on Business Value of Big Data Analytics

Big data analytics involves various analytics techniques (e.g., descriptive analytics and predictive analytics), process, and analytical people embedded in transformation of data that used to support decision-making processes and organizational practices (Davenport & Harris, 2007; Watson, 2014). Implementing big data analytics successfully in an organization is not purely a technological issue but more about organizational procedures, capabilities, and cultures and the ways data-savvy professionals to harness data. To unveil the mystery of the role of big data analytics in creating business value, lately there has been a small number of papers focused on developing big data analytics success models that generally grounded on either variance theories (e.g., Cao et al., 2015; Chasalow & Baker, 2015, Trkman et al., 2010) or process theories (e.g., Shanks & Bekmanedova, 2012; Tamm et al., 2013), as summarized in Appendix A.

Variance theories are aimed to predict levels of dependent variables from levels of contemporaneous predictor variables (Markus & Robey, 1988). The main proposition of variance theories is that each independent effect is affected by each single cause. Variance theories are based on a model or a hypothesis that is compatible with causal explanation and theoretical logic that allows the use of statistical methods to examine an outcome that is determined by a specific value of its predictors. By analyzing big data analytics successful stories from IT vendors, for example, Seddon et al. (2012) develop long-term and short-term big data analytics models to identify critical factors leading to organizational benefits. In the short-term models, big data analytics capabilities (i.e., functional fit of big data analytics tools and readily available high-quality data), analytical people, and overcoming organizational inertia have been delineated as the predictors positively influencing benefits in the on-going big data analytics improvement projects. On the other hand, they treat analytic leadership, enterprise-wide analytics orientation, well-chosen targets, and evidence-based decision making as the key factors for gaining long-term organizational benefits from analytics use. Wixom et al. (2013) have explored two key factors – speed to insight and pervasive use – and their underlying dimension for maximizing big data analytics value from a fashion retailer case.

Some studies develop their big data analytics success models based on process theories. Process theories trace triggers and manifestations in a predefined period of a phenomenon and explain how the outcome changes over time (El Sawy et al., 2010; Mikalef, Pateli, Batenburg, & van de Wetering, 2015). Process theories assume predictors are insufficient but necessary conditions to cause the outcome. Outcomes in the process theories are partially predictable from knowledge of process, not from the level of predictor variables (Markus & Robey, 1988). For example, the models espoused by process theories (e.g., LaValle et al., 2011; Shanks & Bekmamedova, 2012; Sharma et al., 2014; Tamm et al., 2013) have explained how firms can boost their organizational performance by transforming their decision-making processes enabled by big data analytics over time, and further explored the paths to values starting from analytic capabilities through insights, decisions, competitive actions, to organizational benefits.

To summarize, the studies anchoring on variance theories exhibit a set of direct antecedents of big data analytics success, with each antecedent assumed to have independent and direct effects that lead to the variance explained in creating business value. On the other hand, process theories are helpful for recognizing the complexity of causal pathways over time. Studies applying either one of these theoretical lens could be found in the big data analytics literature, which means that in some cases various potential factors are presented and in others paths leading to big data analytics success. However, the combination of both or models examining complex interactions and holistic interplays among these factors has yet to be proposed. To answer our research questions pertaining to the illustration of such complex system, we apply configuration view.

Configuration view on business value of IT research

Configuration view emerging from organizational research and strategic management has the potential to fuel the next jump in the understanding of business value of big data analytics by complementing the potential incompleteness of both process theories and variance theories (Fiss, 2007; Fiss, Marx, & Cambré, 2013). Configuration is the core concept of this theory, which is defined as "a specific combination of causal elements or conditions that generate an outcome of interest" (El Sawy et al., 2010, p. 838). Configuration view allows researchers to understand a complex messy phenomenon by exploring its patterns and combinations of interconnected elements and reveal how its synergistic effects result in specific outcomes. Configuration view also supports the concept of equifinality where the same outcome can be generated by one or more sets of configuration patterns (Fiss, 2007; Ragin, 2008), which can provide new heuristic insights for big data analytics implementation by suggesting multiple strategic configurations from which managers can choose the optimal solution that fits their organizational context (Park & El Sawy, 2013).

Accommodating complex interconnectedness of multiple elements, configuration view can surmount the traditional reductionism problem, (Meyer et al., 1993). For example, El Sawy et al (2010) argue that acquiring strategic advantage in turbulent environments is complex, and IT resource by itself is not enough to explain this complexity. El Sawy and his colleagues examine how IT systems, dynamic capability, and environmental turbulence interact as a three-way tango of digital ecodynamcis that produces strategic advantages in turbulent environments. Based on the same logic, Henfridsson and Bygstad (2013) identify three key mechanisms of digital infrastructure evolution: innovation, adoption, and scaling from 41 cases and then develop a configurational perspective of digital infrastructure evolution to understand how three generative mechanisms contingently lead to evolution outcomes.

The application of configuration view in the IS field is still in its infancy (Park & El Sawy, 2013). To the best of our knowledge, there are no empirical studies examining business value of big data analytics from a configuration view although conceptual papers can be found in the literature (e.g., Kung et al., 2015). As business value generation is a complex process resulting from multi-way interactions among multiple elements, we posit that configuration view is best suited for this study, and consequently use the analysis method designed for this type of study, Qualitative Comparative Analysis (QCA). QCA is a set-theoretic method that has been developed to properly capture the holistic nature of configurations theory and to determine how configurations that present the essential causal ingredients in sets are linked to specific outcome (Fichman, 2004). QCA permits exploring the interplay of elements rather than showing the value of each factor contributing to the outcome.

Expanding from resource-based theory (RBT) of the firm (Barney, 1991),complementarity theory (Ennen & Richter, 2010; Milgrom & Roberts 1995) denotes that the total economic value will be added by combining two or more different resources that exceeds the value generated by these factors in isolation. This theory echoes a similar recognition in the IS literature, especially in business value of IT and IT innovation research. Melville et al. (2004) and Tanriverdi (2005) stress that while IT resources are distinct they are also interdependent and mutually support and reinforce each other. With this logic, Tanriverdi (2006) validates the effects of information technology synergies ascribed to the combination of IT resources that include IT infrastructure, IT strategy, IT human resource, and IT vendor management. Other studies (e.g., Fichman, 2004; Fichman et al., 2014; Melville et al., 2004; Nevo & Wade, 2010) emphasize that various complementarities such as organizational culture, policies and rules, organizational structure, and environmental conditions can interact with IT to achieve superior organizational performance. To better understand the role of big data analytics in creating business value, it is useful to examine the configurations of big data analytics-enabled IT capabilities with other organizational elements in the process of business value generation.

Theoretical Foundation and Research Model

Business value of IT is defined as "the organizational performance impacts of information technology at both the intermediate process level and the organization-wide level, and comprising both efficiency impacts and competitive impacts" (Melville, Kraemer, & Gurbaxani, 2004, p. 287). An IT business value generation framework proposed by Melville et al. (2004) elaborates that business value of IT can be intensified by the bundling of resources (i.e., technology IT resources, human IT resources, and complementary organizational resources), business processes synthesis and integration. This framework expands and deepens the understanding of resource-based theory in the IT context by specifying underlying mechanisms of how IT resource is applied within business processes to improve organizational performance. Meanwhile, a set of propositions were proposed to explain that the inimitability of rare organizational resources complementary to technological IT resources and human IT expertise has great potential to improve operational efficiency of business processes, which in turn spurs economic value for a focal firm.

We employ Melville et al.'s (2004) IT business value generation framework as the underlying theoretical framework for exploring business value driven by big data analytics. We do not intend to strictly follow this framework to develop our research model rather only rely on their logics and rationales to justify the key dimensions and constructs we selected. Following Scyryen (2013), we intend to extend this framework from "business value should be rooted in the identification of IT resources" to "seeking for the best configuration of possible IT resources." This shift will show that various IT resources and complementary organizational resources and capabilities affect each other and can co-create business value. However, the complexity interactions among IT resources and complementary organizational resources and capabilities remain unclear since no theory of IT business value is provided to explain this new perspective (Schryen, 2013).

Our research model thus relied on the configuration view to disentangle the complex interactions among the elements leading to quality of care. Configuration view is better suited for understanding patterns and combinations of factors and how they, as configurations, cause specific outcomes to occur in a certain context (Fiss, 2007; Meyer et al., 1993; Ragin, 2008). This configurational perspective provides the basis for our analysis of the causal paths that explain how, in health care context, the combination of big data analytics capabilities and other organizational elements may lead to superior business value. Specifically, we examine elements of big data analytics capabilities (i.e., traceability, analytical capability, decision support capability, predictive capability, analytics personnel's technical skills, and business skills), complementary organizational resources (i.e., evidence-based decision making culture and data governance), and organizational capabilities embedded in business process (i.e., dynamic, and improvisational capabilities) that can be combined into potential configurations to result in business value of big data analytics. Figure 1 illustrates the interactions among these three configuration elements of big data analytics through intersecting orbits as the holistic confluence that subsequently contributes to enhance quality of care in healthcare. We describe these ten elements, which are included in our configurational analysis for achieving quality of care through big data analytics.

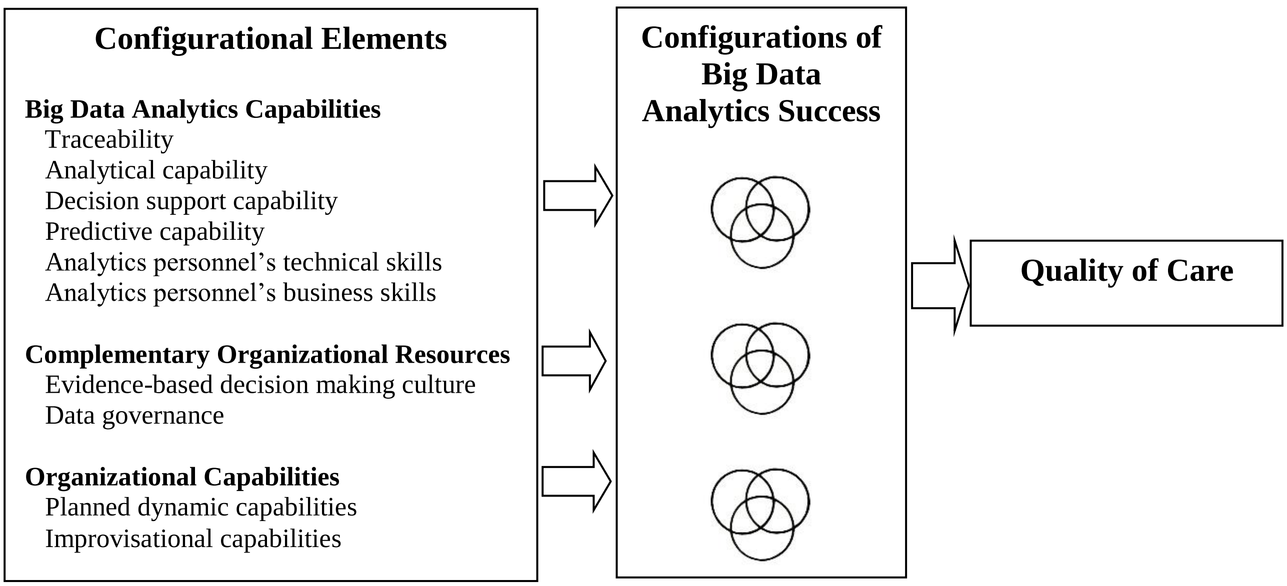


Figure 1. Configurational Model

The Elements of Big Data Analytics Capabilities

The role of big data analytics capabilities in creating superior business value has been emphasized from previous studies (e.g., Cao et al., 2015; Trkman et al., 2010). Big data analytics capability is defined as the ability to acquire, store, process and analyze large amount of data in various forms, and deliver meaningful information to users that allows them to discover business values and insights in a timely fashion (Davenport & Harris, 2007; Watson, 2014). We identified the four generic categories of big data analytics capabilities in our review of the big data implementation cases[1]: traceability, analytical capability, decision support capability, and predictive capability as well as recognized analytics personnel's technical skills and business skills from the existing literature. These are described in turn below.

Traceability

Traceability is the ability to track output data from all the system's IT components throughout the organization's service units. Healthcare-related data such as activity and cost data, clinical data, pharmaceutical R&D data, patient behavior and sentiment data are commonly collected in real time or near real time from payers, healthcare services, pharmaceutical companies, consumers and stakeholders outside healthcare (Groves et al., 2013). Traditional methods for collecting, storing, and disseminating these data are insufficient when faced with the volumes experienced in this context, which results in unnecessary redundancy in data transformation and movement, and a high rate of inconsistent data. On the other hand, big data analytics platforms enable authorized users to gain access to large national or local data pools and capture patient records simultaneously from different healthcare systems or devices. This not only reduces conflicts between different healthcare sectors, but also decreases the difficulties in linking the data to healthcare workflow for process optimization.

The primary goal of traceability is to make data consistent, visible and easily accessible for analysis. Traceability facilitates monitoring the relation between patients' needs and possible solutions through tracking all the datasets provided by the various healthcare services or devices in hospitals. For example, the use of remote patient monitoring and sensing technologies has

[1] In the first essay, we reviewed 33 case descriptions covering 28 healthcare units or systems that adopted big data analytics. The frequency of each big data analytics capability presented in Table3 in the first essay.

become more widespread for personalized care and home care in U.S. hospitals. Big data analytics, with its traceability, can track information that is created by different devices in real time, such as the use of Telehealth Response Watch in home care services. This makes it possible to gather location, event and physiological information, including time stamps, from each patient wearing the device. This information is immediately deposited in appropriate databases (e.g., NoSQL and the Hadoop distributed file system), with excellent suitability and scalability for review by medical staff when needed. Similarly, incorporating information from radio frequency identification devices (RFID) into big data systems enables hospitals to take prompt action to improve medical supply utilization rates and reduce delays in patient flow. A case study at Brigham and Women's Hospital (BWH) provides a typical example of the use of in-depth traceability in large longitudinal healthcare databases to identify drug risk. By integrating big-data algorithms into the legacy IT systems, medical staff can automatically monitor drug safety by tracking warning signals triggered by alarm systems.

Analytical Capability

An analytical process in a big data analytics starts by acquiring data from both inside and outside of the healthcare sectors, storing it in distributed database systems, filtering it according to specific discovery criteria, and then analyzing it to integrate meaningful outcomes for the data warehouse. Analytical capability is defined as the ability to process data with an immense volume (from terabytes to exabytes), variety (from text to graph) and velocity (from batch to streaming) via unique data storage, management, analysis, and visualization technologies. Analytical capabilities can be used to identify patterns of care and discover associations from massive healthcare records, thus providing a broader view for evidence-based clinical practice.

Healthcare analytical systems provide solutions that fill a growing need and allow healthcare organizations to parallel process large data volumes, manipulate real-time, or near real time data, and capture all patients' visual data or medical records. In doing so, this analysis can identify previously unnoticed patterns in patients related to hospital readmissions and support a better balance between capacity and cost. Interestingly, analyzing patient preference patterns also helps hospitals to recognize the utility of participating in future clinical trials and identify new potential markets.

In addition to identifying the patterns of care, analyzing unstructured health data is another key capability in a big data analytics system. Unstructured and semi-structured data refer to information that can neither be stored in a traditional relational database nor fit into predefined data models, such as XML-based electronic healthcare records (EHRs), clinical images, medical transcripts, and lab results. Most importantly, the ability to analyze unstructured data plays a pivotal role in the success of big data in healthcare settings since 80% of health data is unstructured. According to a 2011 investigation by the TDWI research, benefits of analyzing unstructured data capability are illustrated by implementing targeted marketing successfully, providing revenue-generating insights, and building customer segmentation. In the context of healthcare, Leeds Teaching Hospitals in the UK analyze approximately one million unstructured case files per month, and have identified 30 distinct scenarios for improvement in either costs or operating procedures by taking advantage of natural language processing (NLP). This unstructured data analytical capability enables Leeds to improve efficiency and control costs through identifying costly healthcare services such as unnecessary extra diagnostic tests and treatments.

Decision Support Capability

Decision support capability emphasizes the ability to produce reports about daily healthcare services to assist managers' decisions and actions. In general, this capability yields sharable information and knowledge such as historical reporting, executive summaries, drill-down queries, statistical analyses, and time series comparisons. Such information can be utilized to provide a comprehensive view to support the implementation of evidence-based medicine, to detect advanced warnings for disease surveillance, and to develop personalized patient care. Some information is deployed in real time (e.g., medical devices' dashboard metrics) while other information (e.g., daily reports) are presented in summary form.

Reports generated by the analytics engines of big data systems are distinct from those in transitional IT systems, showing that it is often helpful to assess past and current operation environment across all organizational levels. Big data analytics reports are created with a systemic and comprehensive perspective and the results evaluated in the proper context to enable managers to recognize feasible opportunities for improvement, particularly regarding long-term strategic decisions. For example, Premier Healthcare Alliance collects data from different departmental systems and sends it to a central data warehouse. After near-real-time data processing, the reports generated are then used to help users recognize emerging healthcare issues such as patient safety and medication use.

Predictive Capability

Predictive capability is the ability to apply diverse methods from statistical analysis, modelling, machine learning, and data mining to both structured and unstructured data to determine future outcomes (Zikopoulos, Eaton, deRoos, Deutsch, & Lapis, 2012, p. 289).

Wessler (2013) defines predictive capability as “the process of using a set of sophisticated tools to develop models and estimations of what the environment will do in the future” (p. 21). Both these definitions focus on the importance of predicting future trends and insights for organizations and individuals by identifying gaps between current and future states. Predictive analysis makes it possible to cross reference current and historical data to generate context-aware recommendations that enable managers to make predictions about future events and trends. This capability relies on predictive analytical engines that incorporate a data warehouse, a predictive platform with predictive algorithms (e.g., decision trees, neural networks, and logistic regression), and a predictive interface that provides feedback and recommendations to users. Predictive capabilities can assess current healthcare service situations to help managers disentangle the complex structure of clinical cost, identify best clinical practices, and gain a broad understanding of future healthcare trends based on an in-depth knowledge of patients’ lifestyles, habits, disease management and surveillance.

Predictive capabilities can reduce degree of uncertainty, enable managers to make better decisions faster and hence support preventive care. The Texas Health Harris Methodist Hospital Alliance, for example, analyzes information from medical sensors to predict patients’ movements and thus provide needed services more efficiently. It also monitors patients’ actions throughout their hospital stay to reduce medical risk. Healthcare entities with superior big data predictive capabilities should be able to leverage predictive reports to improve decision-making, optimize existing operations and provide high quality healthcare services. For example, I+Plus, an advanced analytical solution used in an Australian healthcare organization, consists of powerful analytical tools for three levels (claims, aggregated data, and admission) of analysis (Srinivasan & Arunasalam, 2013). It provides claim-based intelligence to facilitate customers claim governance, balance cost and quality, and evaluate payment models. Specifically, through these analytical patterns managers can review a summary of cost and profit related to each healthcare service, identify any claim anomalies based on comparisons between current and historical indicators, and thus make proactive (not reactive) decisions by utilizing productive models.

Analytical personnel skills

The role of analytical personnel is considered as a human IT resource in shaping the value of big data analytics (Tamm et al., 2013). Managers and employees with relevant professional analytical competencies is a crucial element of big data analytics success since incorrect interpretation of the reports generated could lead to serious errors of judgment and questionable decisions. Indeed, the success of a big data analytics project depends on the extent to which analytical people have the abilities to understand overall business environment and specific organizational context from data. Surprisingly the importance of analytical personnel as an enabler of big data analytics success has not been emphasized in the existing literature.

Analytical personnel is defined as the organizational members who have an analytic mindset and help drive business value from big data analytics (Davenport et al., 2010). By definition, analytical personnel is a hybrid role that requires a broad combination of technical and soft skills from multidisciplinary knowledge domains. The skill sets for analytical personnel have been investigated in the literature. For example, based on the different levels of data analytical skills, Wilder and Ozgur (2015) categorize analytical people as data scientist, data specialists, and big data analyst. Data scientist is defined as people who understand how to seek for answers to important questions from tsunami of unstructured information (Davenport & Patil, 2012). Data specialists are people who not only have a solid foundation in computer science, mathematics and management, but also understand how data is managed (Wilder & Ozgur, 2015). Business analysts (i.e., chief data officer) are key leaders in the organization responsible for establishing data quality governance and using data-driven insights to make sound decisions, identifying, exploiting business opportunities and addressing business problems (Lee et al., 2014). Skills such as technical skills (e.g., the ability to data storage/extraction, SQL, data warehousing, and Hadoop) and business skills (understanding business issues listening to what the business needs, communication & presentation, teamwork) needed for well-qualified analytics people are summarized in Appendix B. Accordingly, data-savvy professionals with strong skills working together as a team can lead the effort to build organizational capability that can energize and sustain the entire organization and extended enterprise (Lee et al., 2014).

The six big data analytics capabilities elements discussed above - traceability, analytical capability, decision support capability, predictive capability , analytics personnel's technical skills, and soft skills - are related while distinct to each other. Firms have to learn how to effectively combine these big data analytics capabilities to obtain and sustain business value. For example, combining the analytical capability of big data analytics systems and strong analytics people's interpretation skills may provide new tools to improve physicians' diagnoses and treatment decisions, and in turn offering more reliable care to patients. Further, big data analytics capability elements by themselves as independent factors may not reflect the mechanism of the influence of big data analytics implementation on an outcome of interest. Instead, their interactions and combinations with other organizational elements such as complementary resources and organizational capabilities may determine their role on business value (El Sawy et al., 2010; Melville et al., 2004; Ragin, 2008). Therefore, we include a set of other organizational elements that may influence business value along with the aid of these big data analytics capability elements for a more complete and holistic internal view.

The Elements of Complementary Organizational Resources

To implement big data analytics to create business value, organizations will undergo adjustments or even dramatic changes regarding day-to-day operations, data policies, and organizational culture (Brynjolfsson et al., 2012; Davenport et al., 2010; LaValle et al., 2011). Complementary organizational resources related to big data analytics are the requirements for being successful with big data analytics during its implementation (Watson, 2014). Especially in healthcare, such resources can help healthcare organizations face the challenges regarding standardization of various types of data across various healthcare systems and resource integration that requires collaboration and leadership from the public and private sectors (Shah & Pathak, 2014).

Big data analytics-enabled complementary organizational resources are regarded as a specific type of organizational resources that tends to be tacit, idiosyncratic, and deeply embedded in the organization. Scholars have identified several key complementary organizational resources in the context of big data analytics such as enterprise-wise analytics orientation (Davenport & Harris, 2007; Seddon et al., 2012) and fact-based decision-making culture (Seddon et al., 2012; Watson, 2014). In this study, we propose to include two organizational resources, evidence-based decision making culture and data governance in our model for the configurations lead to better quality, that is, business value in healthcare. We present these two organizational resources next.

Evidence-Based Decision Making Culture

Organizational culture is defined as a set of collective values, beliefs, norms, and principles shared among organization members by defining appropriate behavior for various situations (Needle, 2010; Ravasi & Schultz, 2006). Organizational culture has long been recognized as an important role for organization performance by management and strategy scholars. This study focuses on a particular aspect of organizational culture from big data analytics perspective, namely evidence-based decision marking culture, defined as a culture of embracing evidence-based management and embedding evidence-based decision marking in the core values and processes of the organization (Davenport & Harris, 2007; Davenport et al., 2010). Some scholars describe this concept as an information orientation culture that business executives have a heightened awareness of information and information management as they make decisions or formulate business strategies (Kettinger, Zhang, & Marchand, 2011) while others view it as a data-driven culture, defined as "a pattern of behaviors and practices by a group of people who share a belief that having, understanding and using certain kinds of data and information plays a critical role in the success of their organization" (Kiron et al., 2012: 12)

An evidence-based decision making culture inspires an organization to measure, test, and evaluate quantitative evidence (Davenport, 2006; Kiron et al. 2012). Popovič et al. (2012) found that an analytical decision-making culture positively affect the quality of information provided by business intelligence systems. As delineated by Ross et al. (2013), building an evidence-based decision making culture in an organization requires giving all levels of decision makers performance metrics that come from one undisputed source, near real-time feedback, articulating business rules and updating them with new facts, and providing high quality coaching to decision makers on a regular basis.

A healthcare organization with an evidence-based decision making culture would allow incorporating available information within any decision-making process to make better use of real-time data and unify all patients' medical records for making more accurate diagnoses and better treatment decisions and offer more reliable care to patients. An example, reported by IBM, is The Rizzoli Orthopedic Institute in Bologna, Italy, who analyzes patients' genomic data, detailed tests images and case histories to determine hereditary diseases risks and to provide information of effective treatments for hereditary diseases. Their culture allows physicians to develop more evidence-based surgery protocols for patients with genetic disease, resulting in 30% cost reduction of surgery-related hospitalizations and 60% reduction in imaging requests, and optimizing patients' follow-up treatment scheduling. Thus, it is conceivable that evidence-based decision making culture plays a critical enabler of business strategy and a source of business value creation in health care.

Data Governance

Experts have realized that data governance practice is crucial for deriving business value (Khatri & Brown, 2010). Data governance that is built on IT governance aims for formulating data rules and policies and providing a vision and guidelines relating to privacy, security, lifecycle, and ownership of data by aligning the objectives of multiple functions (Kooper et al., 2011; LaValle et al., 2011). Typically, data governance framework is comprised of master data management (MDM), data life cycle management, and data security and privacy management (Wang et al., 2015). Master data management is the processes, governance, policies, standards, and tools for collecting, aggregating, matching, consolidating, quality-assuring, persisting and distributing data throughout an organization (Loshin, 2010). The key aim of master data management is to ensure that data is properly standardized, removed, and incorporated to create the immediacy, completeness, accuracy, and availability of data for supporting data analysis and decision making. Data life cycle management is the process of managing business information throughout its lifecycle, from archiving data, through maintaining data warehouse, testing and delivering different application systems to deleting and disposing of data (Jagadish et al. 2014). Data security and privacy management is the platform for providing enterprise-level data activities in terms of discovery, configuration assessment, monitoring, auditing, and protection (IBM, 2012). Khatri and Brown (2010) propose a hierarchical framework that includes five interrelated decision domains: data principles, data quality, metadata, data access, and data lifecycle for assessing the effectiveness of data governance as implementing big data analytics in an organization.

The key to successful data governance is not technology or methods; instead, it is about practices and people in the organization and their complex ownership of the data that big data analytics initiative will affect. Scholars describe this concept as an organization's data-driven environment that "is the organizational practices reflected by developing explicit data strategy and policy to guide analytic activities and designing its structure and process to enable and facilitate big data analytics activities" (Cao et al., 2015: 2). Data governance can also be viewed as a set of policies, a way of working, or a framework of optimizing the value of information in some sense to the decision makers involved (Kooper et al., 2011). In hospitals, for example, establishing rigorous data policies and data access control mechanisms for highly sensitive healthcare data can prevent security breaches and protect patient privacy. By adopting suitable data policies, standards, and compliance requirements will ensure the systems satisfies healthcare regulations and creates a safe environment for the proper use of patient information. Therefore, we include data governance as an important element in configurations of achieving business value.

The Elements of Organizational Capabilities

To achieve the vast potential of big data analytics not only will enterprise IT architectures need to change, but almost every department within a company will also undergo adjustments (Davenport et al., 2010). Managing big data analytics to get value is not a simple technical issue per se, but a managerial and strategic one (Mcafee & Brynjolfsson, 2012). There are multiple factors involved such as organization capabilities in dealing with unexpected challenges, a new mind set, and even a new strategy.

Organizational capabilities are the significant predictors of business value creation in various contexts (Pavlou & El Sawy, 2006; 2010; Zhu, 2004). In general, organizational capability is defined as the ability to adapt ongoing changes in the business processes and functional activities of the firm (Luo, Fan, & Zhang, 2012), while it is also described as “an organization’s ability to create value in a unique way by utilizing resources” (Wu & Hu, 2012, p. 981) from the RBV perspective. Organizational capabilities such as dynamic capability and improvisational capability typically play an enabler or a mediator role in linking IT to business value (Pavlou & El Sawy, 2006; 2010; Wu & Hu, 2012). Extending the theoretical perspective from strategic alignment between IT and business to co-evolution, some IS strategy studies have suggested that the key to successful health information technologies (HIT) implementation is to orchestrate the complex and dynamic interactions between organizational capabilities and HIT during the business process (Agarwal et al., 2010; Goh, Gao, & Agarwal, 2011; Novak et al., 2012). Although these studies have noted the systemic notion of co-evolution among individual elements for IS success, examining the effect of co-evolution with conventional correlation-based linear methods (e.g., two-way correlations, testing moderator/mediator effect) does not allow taking a holistic view and capturing the non-linear interdependent interactions among these elements.

From a dynamic capability perspective, two types of distinctive organizational capabilities - planned dynamic capability and improvisational capability – have been identified from the core business processes for boosting business value (Pavlou & El Sawy, 2010). Further, with a configurational lens, El Sawy et al. (2010) highlight the role of IT systems in shaping these two capabilities and inducing environmental turbulence to build strategic advantage within digital ecosystems.

Planned dynamic capability is a firm's organizational ability to integrate, reconfigure, gain and renew resources to match rapidly-changing market environments (Eisenhardt & Martin, 2000; Helfat & Peteraf, 2003; Teece et al., 1997; Winter, 2003), and enhance a firm's agility (Roberts & Grover, 2012). Barreto (2010) and Teece (2007) view dynamic capability as the ability to sense and shape opportunities and threats, to seize market opportunities and to maintain competitiveness. *Improvisational capability* is defined as an organization's learned ability to respond to unexpected environmental turbulences quickly by simultaneously forming and executing novel solutions by reconfiguring available resources (El Sawy & Pavlou, 2008). Research from both strategic and organizational management fields has emphasized the importance of organizational improvisation to handle extreme competition, cope with changing circumstances, and pursue potential business opportunities (e.g., Akgun et al., 2007; Barrett, 1998; Bergh & Lim, 2008; Hadida & Tarvainen, 2014; Weick, 1998). Improvisational capability plays a crucial role in building organizational agility to react to market changes. Such “spontaneous” capabilities enable organizations to make effective and real-time decisions in response to turbulences without having to go through formal planning channel. We include planned dynamic capability and improvisational capability as two important organizational capabilities for achieving business value with big data analytics.

Research Methodology

For this study, healthcare industry was selected as our research context for two reasons: (1) big data analytics implementation in healthcare industries has lagged behind other industries such as retail and banking. Little is known about whether big data analytics adoption actually contributes to the growth of healthcare while other industries have obtained tremendous benefits driven by big data analytics, and (2) focusing on single industry can mitigate potential confounding effects due to industry nature and variation. We tested our model using a multi-source dataset acquired from a survey and Centers for Medicare & Medicaid Services (CMS) databases. The construct development and measurement, data collection, and data analysis approach are described in detail next.

Data Collection and Sources

An initial population set of 4668 senior IS executives (e.g., Vice Presidents, CIOs, and IT directors) in US hospitals with facility name, job title, phone number, and email address was extracted from the Healthcare Information and Management Systems Society (HIMMS) database. After cleaning up incomplete information and duplicates, 3307 senior IS executives are available. An online survey was designed for this study. An information letter with the description of research purpose and information privacy protection statement with the survey was distributed to potential participants via a survey platform. This platform also provides tracking and reminder functions that helped us track the participants' progress and control the survey schedule. First round of 3307 questionnaires were sent, and immediately 511 emails bounced back due to their organizations' firewall blocking policy, and 1589 emails have not been opened. We sent a gentle reminder after one week. Of the 1027 valid invitations distributed, 65 responses were returned and 63 responses were complete and usable for data analysis, showing a response rate of 6.33 percent.

To test our research model, we use a multi-source dataset obtained from our survey and the Centers for Medicare & Medicaid Services (CMS) databases. From our survey, we have obtained the information regarding the effectiveness of hospital use of big data analytics, the skills of analytics personnel, complementary organizational resources, and organizational capabilities. These are assessed on a seven-point Likert-type scale ranging from 1= strongly disagree to 7 = strongly agree. From the CMS, we have data on actual quality of care for the hospitals as the dependent variables of our study. The dependent variables consist of data on average excess readmission ratio (AERR) and total performance score (TPS). For AERR, we are able to match CMS data to our survey for 34 cases. Another match-up dataset for TPS contains 29 cases.

Measurement Items

Most measurement items were adopted from the literature and modified to fit this study. Efforts were made to use existing validated scales for this study. We developed the measurement items for the four big data analysis capabilities. Outcomes and elements are presented in this section while Appendix C lists the measurement items.

Quality of care: Quality of care is a key component of the business value expected from HIT (Barhan & Thouin, 2013; Menon & Kohli, 2013). To assess the quality of care, we take advantage of the recently released Hospital Compare Data database[2]. This database provides information on how well hospitals provide healthcare service to their patients and allows them to compare performance measure information related to certain conditions. We extracted AERR and TPS from the Hospital Readmissions Reduction Program (HRRP) and Hospital Value-Based Purchasing (HVBP) Program based on applicable period of July 1, 2011 to June 30, 2014. The average excess readmission ratio is used as one of the measures of quality of care (CMS, 2014). A hospital's excess readmission ratio is a measure of a hospital's readmission performance compared to the national average for the hospital's set of patients with that applicable condition. While there are a variety of quality outcome measures that could be considered, we chose excess readmission ratio, as they are a reflection of the total process of care received (Pye et al., 2014). Hospitals can provide the better quality of care if the risk of being readmitted for the same diagnosis in the future is reduced (Bardhan et al., 2015).

The average excess readmission ratio was calculated by the following formulas. The higher the ratio, the worse the quality of care.

(1) *Excess readmission ratio = risk-adjusted predicted readmissions/risk-adjusted expected readmissions*

(2) *Average excess readmission ratio = (Excess Readmission Ratio for Pneumonia + Excess Readmission Ratio for heart failure + Excess Readmission Ratio for acute myocardial infarction + Excess Readmission Ratio for total hip/knee arthroplasty + Excess Readmission Ratio for Chronic Obstructive Pulmonary Disease)/5*

[2] www.medicare.gov/hospitalcompare

Another quality of care is measured by patient satisfaction that is provided by Hospital Value-Based Purchasing (HVBP) program from CMS. This program is part of CMS' long-standing effort to link Medicare's payment system to quality. The program implements value-based purchasing to the payment system that accounts for the largest share of Medicare spending. Hospitals are paid for inpatient acute care services based on the quality of care, not just quantity of the services they provide. From this data, two domains are used to assess hospital performance: 1) Patient experience of care and 2) Clinical process of care. The patient experience of care domain is comprised of the Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) Survey measures. The Clinical Process of Care domain is comprised of selected Inpatient Quality Reporting (IQR) Program's Process of Care measures from the Acute Myocardial Infarction (AMI), Healthcare Associated Infections (HAI), Heart Failure (HF), Pneumonia (PN), and Surgical Care Improvement Project (SCIP) measure sets. A performance score and an improvement score are calculated for each measure, a domain score is then calculated for each of the two domains. The Total Performance Score (TPS) is calculated using the weighted domain scores. The Clinical Process of Care domain score is weighted as 70 percent of the TPS, and the Patient Experience of Care domain is weighted as 30 percent of the TPS.

Big data analytics capabilities: In order to develop our constructs and items properly, content analysis was used to analyze 33 case descriptions covering 28 healthcare units or systems that adopted business analytics. Theses 33 case descriptions were found from the academic journal databases (i.e., ABI/INFORM Complete, Web of Science, and IEEE Xplore Digital Library). Then, a three-phase process for inductive content analysis (i.e., preparation, organizing, and reporting) was performed to capture the statements regarding business analytics capabilities.

Finally, constructs and measurement items were generated after the coding processes and the classification by two coders. We identify four business analytics capabilities: traceability, analytical capability, decision support capability, and predictive capability as well as their underlying items. However, the notion of analytical personnel skill did not recognize from these case materials. Thus, the scales for analytical personnel skills – technical and business skills were identified from previous studies (see Appendix B). We asked senior IS executives to evaluate whether the effective use of business analytics systems and analytical people in their organization can develop these capabilities.

Evidence-based decision making culture: The measurement of this construct was based on a summary of the relevant literature, and, further, are properly adapted to the context of health care as discussed previously (Kiron et al., 2012; Kiron & Shockely, 2011; Popovič et al., 2012; Ross et al., 2013). 5-item scale was used to evaluate organizational decision-making processes of whether organization consider evidence-based insights generated from business analytics to make improvements on current services (Kiron & Shockley, 2011; Kiron et al., 2012) of whether organization have clear business rules and performance feedback mechanism on the basis of business analytics (Ross et al., 2013), and the intention to use information for each decision-making process (Popovič et al., 2012).

Data governance: Data governance enacts a critical role in business analytics implementation to ensure the quality, security, privacy, and lifecycle of data. Organizations have to provide a clear guideline and establish the policies and rules to harness these data throughout the entire organization. This factor was measured with five items from Khatri & Brown (2010), which includes the key data decision domains of data governance framework: data principles, data quality, metadata, data access, and data lifecycle. We asked senior IT executives to evaluate the effectiveness of their data governance regarding these five data decision domains.

Planned dynamic capability: This part of the questionnaire includes four subconstucts: sensing, learning, coordination, and integration capabilities. We adopted the 12-item measurement of Pavlou & El Sawy (2010) and further, modified them properly to fit the healthcare domain. We asked senior IT executives to evaluate the effectiveness by which their organization spontaneously reconfigures its operational capabilities in the healthcare services to address rapidly-changing environments relative to your major competitors.

Improvisational capability: This capability is based on those stated by Moorman & Miner (1998), Pavlou & El Sawy (2006; 2010) as adapted to the healthcare domain, which meld the concept that emphasizes the spontaneous and intuitive recombination of resources in real time to build new operational capabilities in response to a novel situation into our measurement items. We asked senior IT executives to evaluate the effectiveness by which their organization spontaneously reconfigures its operational capabilities in the healthcare services in novel environmental situations relative to their major competitors.

Measurement Validity and Reliability

To assess the validity and reliability of measurements, a sample data set (N=63) collected for this study was used using SmartPLS 2.0 (Ringle et al., 2005). We note that all of the reliability coefficients (Cronbach's alphas) are above 0.70 (see Table 1), showing that the measurements are reliable. Convergent validity was assessed by three criteria: (1) item loading, (2) composite reliability, and (3) average variance extracted (AVE) (Fornell & Larcker, 1981). As shown in Table 2 and Appendix D, the loadings are all in acceptable ranges, and all but one item of those for data governance have loadings above the threshold of 0.7. The one item that has a loading of 0.650, it exceeds another acceptable threshold of 0.6 proposed by scholars (Barclay, Higgins, & Thompson, 1995; Chin, 1998), the composite reliabilities scores range from 0.85 to 0.94. Each AVE is above 0.5 (see Table 1), indicating that the latent construct can account for at least 50 percent of the variance in the items. Moreover, we employed two methods to assess discriminant validity: (1) checking whether each item loads more highly on its assigned construct than on other constructs, as suggested by Gefen et al. (2000) and (2) checking whether each construct's square root of the AVE is greater than its correlations with other constructs (See Table 2) (Fornell & Larcker, 1981). Each item loading in cross-loading table (Appendix D) is much higher on its assigned construct than on the other constructs. The square root of the AVE is greater than all of the inter-construct correlations (Chin, 1998). Thus, our measurement demonstrates sufficient discriminant and convergent validities.

Table 1. Correlations among Major Constructs

Construct	TRA	ANA	DEC	PRE	TS	BS	CUL	DG	DYN	IM
Traceability	**.87**									
Analytical capability	.06	**.91**								
Decision support capability	.19	.25	**.94**							
Predictive capability	.09	.20	.19	**.89**						
Technical skills	.37**	-.21	-.19	.31*	**.88**					
Business skills	.05	.02	.17	.25*	.23	**.81**				
Decision making culture	.14	.16	.17	.03	-.11	.16	**.88**			
Data governance	-.09	.21	-.27*	-.08	.11	.10	-.26*	**.74**		
Dynamic capability	.34**	-.01	.10	.04	.32**	-.08	-.18	-.06	**.86**	
Improvisational capability	-.05	-.42**	.19	.17	-.15	.07	.24	-.09	-.10	**.89**

Note: N=63; Square root of AVE are in bold
*p<0.05; **p<0.01

Table 2. Convergent Validity

Construct	Items	Mean	SD	Loading	Composite Reliability	AVE	Cronbach's α
Traceability	3	4.70	.99	.782 - .886	.90	.75	.85
Analytical capability	3	4.27	1.23	.802 - .913	.94	.83	.90
Decision support capability	2	4.60	1.55	.843 - .907	.94	.89	.89
Predictive capability	3	4.34	1.06	.832 - .867	.92	.79	.87
Technical skills	4	5.13	1.17	.792 - .865	.94	.78	.90
Business skills	3	4.52	.98	.731 - .853	.85	.65	.79
Decision making culture	3	3.80	1.27	.778 - .922	.91	.78	.86
Data governance	5	3.63	.92	.650 - .812	.85	.55	.84

Dynamic capabilities	4	3.55	1.28	.715 - .915	.92	.74	.88
Improvisational capabilities	3	3.58	1.17	.827 - .898	.92	.80	.87
Average excess readmission ratio	-	.999	.058	-	-	-	-
Total performance score	-	40.603	11.452	-	-	-	-

Common Method Bias

To reduce common method bias, Podsakoff and colleagues (2003) suggest utilizing structural procedures during the design of the study and data collection processes. Following these guidelines, we protect respondent-researcher anonymity, provide clear directions, and proximally separate independent and dependent variables (Podsakoff et al., 2003). We then assess the potential effect of common method bias statistically by conducting three tests. First, Harman’s one-factor test (Brewer, Campbell, & Crano, 1970; Podsakoff & Organ, 1986) generated ten principal constructs, and the unrotated factor solution shows that the first construct explains only 16.742% of the variance, indicating that our data do not suffer from high common method bias. Second, we performed a partial correlation technique using a marker variable to eliminate the influence of common method bias. Following Lindell & Whitney (2001), we used the second smallest positive correlation among measurement items (0.01) as a proxy for common method bias to adjust the correlations between the principal constructs. The adjusted correlations were only slightly lower than the unadjusted correlations and their significance levels did not change, suggesting that common method bias did not spuriously inflate the construct relationships (Lindell & Whitney, 2001). Finally, following a procedure suggested by Pavlou et al. (2007), we compared correlations among the constructs. The results revealed no constructs with correlations over 0.7, whereas evidence of common method bias ought to have brought about greatly high correlations (r >.90). Consequently, these tests suggest that common method bias is not a major concern for this study.

Analysis Method: Qualitative Comparative Analysis (QCA)

Moving beyond relying on the dominant logic of regression-based analysis, in the current study, we use the fuzzy-set qualitative comparative approach (Crilly, 2011; Fiss, 2011; Ragin, 2008) to gain new insights for the IT business value generation. An in-depth explanation of this method is beyond the scope of the current study but because fuzzy-set qualitative comparative analysis method is novel in IS field, we provide a brief introduction and list the steps carried out to demonstrate the concept and process.

QCA was developed in political science to evaluate case studies with too few cases for standard statistical analysis and where the available data are often qualitative or a combination of qualitative and quantitative (Ragin, 1987; Rihoux & Ragin, 2009). From its inception, QCA was aimed at the “middle ground” between quantitative and qualitative methodologies (Ragin 2000, p.22). In contrast to statistical regression-based methods, QCA is based on set theory and logic and is designed to evaluate social systems characterized by causal complexity.

QCA belongs to a class of analytic techniques based on set theory called Configurational Comparative Methods (CCMs) (Thygeson, Peikes, Zutshi, 2013, p. 2). QCA is configurational because it allows investigators to identify combinations of configurations associated with an outcome of interest. There are three types of QCA: (1) crisp-set QCA (csQCA), (2) multi-valued QCA (mvQCA), and (3) fuzzy-set QCA (fsQCA). These types differ in how the characteristics are coded. CsQCA codes characteristics in binary (0 and 1). MvQCA require characteristics to be coded as multi-valued (more than two discrete values, usually three) variables. FsQCA allows a characteristic to have any continuous value from 0 to 1. A fuzzy logic conclusion is not “stated as either true or false, but as being possibly true to a certain degree” (Treadwell, 1995, p.93). We chose to apply the fuzzy-set approach because it offers an outlet that using the different degrees of membership in a set, researcher can study and can have more complete view of the phenomenon (Ragin, 2008a).

There are three qualitative anchors in fuzzy set: full membership, full nonmembership, and the cross-over point. Fuzzy sets complement QCA as a methodological tool to translate categorical concepts into measurable conditions, drawing on the notion that cases can hold degrees of membership in a given set (Ragin, 2008a). The building block of fuzzy-set QCA is "fuzzy" membership of cases in a set of cases with a given characteristic. A practice can be fully out of a set (membership = 0), a full member of the set (membership = 1), or a partial member of the set (membership between 0 and 1). In other words, practices can have continuously varying degrees of membership in a given set. The fuzzy set approach provides flexibility for modeling the "fuzziness" implicit in concepts.

In essence, fsQCA takes the perspective that cases are constituted by combinations of theoretically relevant attributes and that the relationships between these attributes and the outcome of interest can be understood through the examination of subset relations (Ragin, 2000, 2008b). The attributes and the outcome are "*best understood in terms of set membership*" (italics in original; Fiss, 2007, p. 1183). For example, in this study, we proposed that different combinations of big data analytics capabilities, complementary organizational resources, and organizational capabilities could explain some portions of the outcome, hospital quality of care. In particular, our exploratory analyses investigate what, if any, combinations of big data analytics capabilities and other organizational elements are sufficient for obtaining higher quality of care.

Data Analysis Procedure using fsQCA

In configurational type of analysis, the “attributes” which are analogical to regression type of analysis as factors or independent variables (IV) are termed “conditions” " or “elements”. In this section, we present the analysis process using fsQCA.

Step 1: calibration of set memberships

After case selection, a critical requirement in QCA analysis is to carefully convert data into measures of set membership using theoretical or substantive knowledge external to the empirical data—a process called calibration. It is a process of transforming interval scale values to fuzzy set membership scores based on three qualitative anchors: full membership, full non-membership, and the crossover point of maximum ambiguity regarding membership in the set of interest (Rai, Patnayakuni, & Seth, 2006). The set membership score represents the extent to which each case is a member of, for example, high level of tractability capability.

In creating decision rules for calibration, the investigator can use a variety of techniques to identify cutoff points or anchors. For qualitative conditions, the investigator can define decision rules by drawing from the literature and knowledge of the intervention context. For conditions with numeric values, the investigator can also employ statistical approaches. Ideally, when using statistical approaches, a researcher should establish thresholds using substantive knowledge about set membership (thus, translating variation into meaningful categories).

We followed Ragin (2008a) in calibrating fuzzy-set memberships. For each calibration, we set thresholds based on industry common standards if available, extant theory or substantive knowledge. We used the direct method of calibration in the fsQCA software to transform the measures into set memberships (e.g., Fiss, 2011; Ragin, 2008a). Survey items that are on Likert scale have somewhat built-in membership scores. All conditions were measured using a 1-7 scale so we calibrate them using 6, 4, 2 as the full membership, the crossover point, and the full non-membership anchors respectively.

As aforementioned, we use average excess readmission ratio and TPS as our outcomes. For both measures of quality, we calculated the national average and their standard deviation respectively. For the first measure of quality of care using average excess readmission ratio, we set up a “low average excess readmission ratio” set because the lower the ratio the better the quality. A national excess readmission ratio average was calculated by taking the mean of the rate from over 3,500 hospitals across the country as the industry standard and the base value to evaluate the memberships. We also calculated the standard deviation. The cut-off point for the full membership for this set is then set as the result of the national average excess readmission ratio minus 1SD, which is 0.92. The anchor for 0.99 for the cross-over point is .99, the national average excess readmission ratio. And the cut-off point for the full non-membership is set at the value of national average excess readmission ratio plus 1SD, 1.10.

For the second measure of quality, we set up a "high TPS" set because as most performance measures the higher the score the higher quality. Two domains, patient experience of care and clinical process of care are used to assess hospital performance: A performance score and an improvement score are calculated for each measure, a domain score is then calculated for each of the two domains. The Total Performance Score (TPS) is calculated using the weighted domain scores. The Clinical Process of Care domain score is weighted as 70 percent of the TPS, and the Patient Experience of Care domain is weighted as 30 percent of the TPS. Using the same statistical measures, the cutoff point for fully in the high TPS set is 53.14 (national TPS plus 1SD), 40.48 for the cross-over point (national TPS), and 27.82 (national TPS minus 1SD), and) as the fully not-in-the-set point.

The configuration conditions selected for this study are: the four business analytics capabilities, two analytics personnel's skills, two complementary organizational resources (i.e., evidence-based decision making culture and data governance), two organizational capabilities (i.e., planned dynamic capabilities and improvisational capabilities). All the items for the variables except the business analytics capabilities are extracted from literature and validated scales. This study uses a 7-point Likert scale for construct survey items: 1= lowest, 4= neutral, 7= highest level. We therefore set up the high level membership sets using 6 as the fully in the set cutoff point, 4 as the cross over point, and 2 as fully not in the set point. Table 3 summarizes the fuzzy set calibration rules.

Table 3. Overview of the Calibration Rules for Elements and Outcomes

Constructs	Calibration rule	
Big data analytics capabilities (BAC) Traceability Analytical capability Decision support capability Predictive capability Analytics personnel's technical skills Analytics personal's business skills	If BAC > = 6 If BAC < = 2 If BAC = 4	1 (full membership) 0 (full non-membership) 0.5 (cross-over point)
Complementary organizational resource (COR) Evidence-based decision making culture Data governance	If COR > = 6 If COR < = 2 If COR = 4	1(full membership) 0 (full non-membership) 0.5 (cross-over point)
Organizational capability (OC) Planned dynamic capabilities Improvisational capabilities	If OC > = 6 If OC < = 2 If OC = 4	1 (full membership) 0 (full non-membership) 0.5 (cross-over point)
Low Average excess readmission ratio (AERR)	If AERR <= .92 If AERR > 1.1 If AERR = .99	1 (full membership) 0 (full non-membership) 0.5 (cross-over point)
High total performance score (TPS)	If TPS > = 53.14 If TPS < = 27.82 If TPS = 40.48	1 (full membership) 0 (full non-membership) 0.5 (cross-over point)

Sept 2: Run the fuzzy truth table algorithm

After calibration, sets are ready for the fuzzy truth table analysis in relations of the configuration conditions and the outcome. Scholars suggest to test what conditions might be necessary for the outcome before analyzing sufficiency (Legewie, 2013). A “necessary" condition is defined as that the outcome would not have happened without it. We assessed necessary conditions for the two quality of care measures by running the necessary condition analysis option on fsQCA. We then check the consistency scores. If the consistency score for a certain condition is above 0.9 then we can categorize it as a necessary condition. After the necessary conditions analysis, we then run the truth table algorithm by choosing the outcome and conditions. We used standard analysis procedure on fsQCA. Frequency and consistency cut-off points are then specified. This process clarifies any relationships between combinations of potentially causal or descriptive characteristics and the outcome of interest.

Sept 3: Present the result

The output of fuzzy-set truth table analysis is one or more combinations of characteristics associated with an outcome. We present the results in the next section.

Results of fsQCA analysis

This section presents the configurations that resulted from fsQCA analysis of low average excess readmission ratio and high total performance score, as shown in Table 4 and 5, respectively. The configurations are expressed by the notation systems from Ragin and Fiss (2008). The filled circles indicate the presence of an element, which is central core elements in a configuration, while empty circles are peripheral elements (supportive roles) that have rather weaker causal relationship with the outcomes. Crossed-out circles indicate the absence of an element (or condition). Blank space indicates a "don't care" situation, which means that the causal element may be either present or absent. For example, the filled circle for analytical capability in solution recipe #1 on Table 4 means that a high level of analytical capability is present with the outcome of low readmission rate, while the crossed-out circle of traceability in solution 2 means that a high level of traceability is absent for solution 2.

This study sets the minimum acceptable frequency of cases for solutions at 1 and the lowest acceptable consistency cutoff at 0.75, which meets the recommended minimum threshold of 0.75 (Ragin, 2008a). Five different configurations result in low average excess readmission ratio, meaning five different paths could lead to the same outcome (see Table 4). Four different configurations result in high total performance score, meaning four different paths could lead to this outcome (see Table 5). This demonstrates the equifinality characteristics of qualitative comparative analysis, that is, we can obtain the same endstate from different starting point and/or combinations of conditions.

Table 4. Configurations for Outcome 1: Low Average Excess Readmission Ratio (N=34 cases)

Elements	**Solution**				
	1	**2**	**3**	**4**	**5**
Big data Analytics Capabilities					
Traceability	○	⊗	○	○	○
Analytical capability	●	●	●	●	●
Decision support capability	●	●	●	●	●
Predictive capability	○	●	○	○	○
Analytics Personnel's Technical skills	○	⊗	○	○	○
Analytics Personnel's business skills	○	⊗	⊗	⊗	○
Complementary Organizational Resources					
Evidence-based decision-making culture		⊗	⊗	⊗	○
Data governance	⊗	⊗	⊗	○	○

Organizational capabilities					
Dynamic capabilities	⊗	⊗	○	⊗	○
Improvisational capabilities	○	⊗	⊗	⊗	○
Consistency	0.803	0.967	0.827	0.897	0.921
Raw Coverage	0.387	0.153	0.212	0.225	0.241
Unique Coverage	0.159	0.036	0.022	0.032	0.053
Overall Solution Consistency	**0.832**				
Overall Solution Coverage	**0.569**				

Note: ●: Central core elements
○: Peripheral elements that have rather weaker causal relationship with the outcome
Blank space: don't care elements
⊗ : The absence of an element (or condition)

Table 5. Configurations for Outcome 2: High TPS (N= 29 cases)

Elements	**Solution**			
	1	**2**	**3**	**4**
Big Data Analytics Capabilities				
Traceability	○	⊗	○	○
Analytical capability	○	⊗	○	○
Decision support capability	●	●	●	●
Predictive capability	○	○	○	●
Analytics Personnel's Technical skills	○	⊗	○	○
Analytics Personnel's business skills	●	⊗	⊗	○
Complementary Organizational Resources				
Evidence-based decision-making culture		⊗	⊗	○
Data governance	⊗	⊗	⊗	○
Organizational capabilities				
Dynamic capabilities	⊗	●	○	○
Improvisational capabilities	○	⊗	⊗	○
Consistency	0.779	0.922	0.724	0.919
Raw Coverage	0.421	0.164	0.209	0.269
Unique Coverage	0.195	0.041	0.015	0.059
Overall Solution Consistency	**0.757**			
Overall Solution Coverage	**0.554**			

In fsQCA, two central measurements provide parameters of fit: consistency and coverage (Ragin, 2008a; b). Consistency measures the degree to which a relation of necessity or sufficiency between a causal condition (or combination of conditions) and an outcome is met within a given data set (Ragin, Charles, Drass & Davey, 2006). It resembles the notion of significance in statistical models (Thiem, 2010, p. 6). Consistency values range from "0" to "1," with "0" indicating no consistency and "1" indicating perfect consistency. Each solution consistency "measures the degree to which membership in each solution term is a subset of the outcome" (Ragin, 2008a, p. 86). As shown in Table 4 and 5, we note that all of the consistency scores for configurations are above the suggested cutoff value of .75 (Legewie, 2013) which suggests that these models (solutions/recipes/configurations) are adequately specified.

Once consistency has been established, coverage provides a measure of empirical relevance (Legewie, 2013). The analogous measure in statistical models would be R^2, the explained variance contribution of a variable (Thiem, 2010, p. 6). Coverage is computed by gauging "the size of the overlap of [...] two sets relative to the size of the larger set" (Ragin & Fiss, 2008, p.57), with values again ranging between "0" and "1". FsQCA analysis presents two types of coverage, the raw coverage and the unique coverage. Raw coverage measures the proportion of memberships in the outcome explained by each term of the solution (Ragin & Fiss, 2008). The results in Table 4 show that, solution 1, 2, 3, 4, and 5 explains 38.7%, 15.3%, 21.2%, 22.5%, and 24.1% of low average excess readmission ratio respectively. Regarding the raw coverage of solutions, the lower the coverage score, the less empirically relevant the causal recipe (Legewie, 2013). Solution 1 has the highest raw coverage score (.387) and the highest unique coverage (.159), indicating that this solution covers more cases in the outcome data set.

For the second outcome, the results in Table 5 reveal that, solution 1, 2, 3, and 4 explains 42.1%, 16.4%, 20.9%, and 26.9% of high TPS respectively. Solution 1 has the highest raw coverage score (.421) and the highest unique coverage (.195).

Unique coverage measures the proportion of memberships in the outcome explained solely by each individual solution term (memberships that are not covered by other solution terms). The unique coverage scores can be used for two interrelated observations: cases uniquely explained by a recipe and overlap between recipes. Unique coverage indicates how many cases a given recipe can explain without any other recipe offering explanation. Solutions with higher unique coverage thus gain relevance because without them more cases would be beyond the explanatory reach of the model (Legewie, 2013).

In Table 4, among five solutions, solution 1 has the highest unique coverage score (.159), indicating that acquiring analytical and decision support capabilities from business analytics systems with the support of other three business analytics capabilities and improvisational capabilities enable healthcare organizations to reduce the average excess readmission ratio in the clinical processes. In Table 5, among four solutions, solution 1 uniquely explains 19.5 % of the variances of high TPS, showing that the high total performance can be achieved by a high level of decision support capability and the cultivation of analytics personnel's business skill.

FsQCA also presents an overall solution coverage and solution consistency. Solution coverage measures the proportion of memberships in the outcome that is explained by the complete solution. Overall solution consistency roughly means that the degree to which these configurations consistently result in high quality of care (Park & El Sawy, 2013). Therefore, the five solutions can consistently explain 83.2 percent of low average excess readmission ratio, while four solutions can consistently explain 75.7 percent of high TPS. Overall solution coverage means that the extent to which these configurations cover high quality of care (Ragin, 2008a). In a fuzzy set relation, it explains what percent of membership for the outcome set can be captured by the configurations. The complete solution can capture 56.9 percent of low average excess readmission ratio and 55.4 percent of high TPS.

Discussion

In this section, we discuss our findings based on each of the outcomes.

Outcome 1: Low average excess readmission rate

We ran the necessary condition analysis for this outcome. Analytical capability and decision support capability are evaluated to be necessary conditions with consistency scores of 0.901 and 0.979 respectively. This implicates that for a healthcare organization to have low readmission rate, they almost always have high analytical capability and high decision support capability.

Five different configurations result in low average excess readmission ratio, meaning that five different paths could lead to this outcome. All solutions have the two necessary conditions then various on different combinations of elements. All the four big data analytics capabilities are either core or contributors in all solutions except traceability is absent in solution 2. The two complementary organizational resources (evidence-based decision making culture, data governance only contribute to solutions 4 and 5.

When a healthcare organization does not have high-level resources such as evidence-based decision making culture, data governance and dynamic capabilities, it must have high level of analytical and decision support capabilities combined with traceability, personnel's technical and business skills, and improvisational capabilities to achieve high level of quality of care (low readmission rate). Interestingly, the evidence-based decision making culture is not present in this solution (#1).

When a healthcare organization lacks high level of traceability, personnel's skills, organizational resources and other capabilities (dynamic and improvisational capabilities), the combination of high level of analytical, decision support and predictive capabilities could lead it to low readmission rate (Solution #2). Another path to better quality of care would be the combination of mainly high levels of analytical and decision support capabilities and supportive roles of high level of traceability, predictive capability, analytics personnel's technical skills and dynamic capabilities, even without high levels of analytics personnel's business skills, decision making culture, data governance, and improvisational capabilities (Solution #3). Interestingly, the difference between solutions #3 and #4 is the "switching" of importance of data governance and dynamic capabilities. With all other elements equal, to get to better quality of care, a healthcare organization either builds its data governance or its dynamic capabilities. Solution 5 seems hard to achieve because it has all the causal elements present; however, it covers 5% of our cases uniquely, which in turn means that there are healthcare organizations that achieve high level of quality of care by building all the big data analytics capabilities with complementary organizational resources, dynamic and improvisational capabilities.

Contradictory to previous studies (e.g., Popovič et al., 2012; Ross et al., 2013), our fsQCA result shows that evidence-based decision making culture is absent in most of solutions (except for solution 5). A possible explanation is that in a healthcare organization especially in a clinic when treating patients most physicians rely on their professional experiences in making decision instead on a system output that they are not familiar with or have not been trained to use it (Watson, 2014).

Outcome 2: High total performance score (Patient satisfaction)

Table 5 shows four paths for healthcare organizations to achieve high total performance. The similarity among these four configurations is the presence of high level of decision support capability from the big data analytics systems, a necessary condition for this outcome with a 0.9.

When a healthcare organization does not have high-level data governance and dynamic capabilities, it must have high level of decision support capabilities from the system and high level of analytics personnel's business skills, supported by system's traceability, analytical capability, predictive capability, analytics personnel's technical skills, and improvisational capabilities to achieve high level of quality of care (TPS). The presence of analytics personnel's business skill such as their healthcare knowledge and organizational skills are very important. With these business skills, analytics personnel can provide more meaningful clinical reports to decision makers. Interestingly, the evidence-based decision making culture is a "don't care" element in this solution (O2S1, Outcome 2 Solution1), which means such culture could be present or absent for this configuration.

O2S2 is very different from O2S1, in terms of the absences of most elements. There are two core elements and one support elements combination for a healthcare organization to achieve high TPS: high level of the decision support capability from big data analytics systems and high level dynamic capabilities, with the supportive role of predictive capability from the big data analytics system. The high level dynamic capabilities does matter for improving patient satisfaction. This solution (O2S2) has the highest consistency of 0.922 which means this configuration consistently shows up in our cases. In other words, most our case organizations do not have high levels of analytics personnel's skills, evidence-based decision-making culture, data governance, or improvisational capabilities. These elements are either hard to build or a more long-term planning from which a short term effect is hard to show.

In the situation that a healthcare organization has high levels of big data analytics system capabilities, analytics personnel's technical skills, and dynamic capabilities for operation, it can get high TPS without high levels of analytics personnel's business, evidence-based decision-making culture, data governance, or improvisational capabilities (O2S3).

O2S4 is identical to O1S5. In this configuration, a healthcare organization has high levels of all the elements presented in this study. It is the ideal goal but not easy to achieve, evidenced by its unique coverage of 5.9%, that there are 2 case organizations achieve high level of TPS with mostly high levels of the big data analytics system's decision support capability and predictive capability, supported by the other two the big data analytics system's traceability and predictive capability, high levels of both analytics personnel's skills (technical and business), and high levels of dynamic and improvisational capabilities.

Worthy of noting is that complementary organizational resources and organizational capabilities Solutions 1, 3 and 4 of this outcome 2 are identical to outcome 1's Solutions 1, 3 and 5 respectively. This phenomenon suggests that with the same combinations of organizational decision making culture, data governance, routine and unplanned operation capabilities, it is the configurations of different levels of big data analytics capabilities that cause a healthcare organization's high quality of care in low readmission rate or TPS in the big data era.

One specific capability facilitated by big data analytics systems, decision support capability, is the common core causal element of our two outcomes. Decision support capability can generate meaningful clinical summary in real time or near real time and presents it using visual dashboards/systems and yields sharable information and knowledge such as historical reports, executive summaries, drill-down queries, statistical analyses, and time series comparisons to different decision makers. Those information assist healthcare analysts to recognize emerging healthcare issues such as medical errors, potential patient safety issues or inappropriate medication use, which in turn they can alert medical professionals and patients. This type of services thereby increases quality of care and patient satisfaction.

Theoretical and Practical Implications

This study is a preliminary attempt to respond to calls in the IS literature to study how IS assets, IS capabilities and socio-organizational capabilities jointly create competitive value (Schryen, 2013, p. 159) by applying configuration logic and fsQCA approach. Scholars have acknowledged that IT, specifically, IT/IS capabilities (e.g., Mueller et al., 2010; Pavlou & El Sawy, 2006; 2010) and IT/human IT resource (e.g., Bradley et al., 2012; Melville et al., 2004) can create value in various contexts. Some research take a step forward and emphasize the particular relationships between IT related elements and organizational elements (organizational capabilities) in the IT business value generation process (Kim et al., 2011; Nevo & Wade, 2010; Pavlou & El Sawy, 2010). Notably, synthesizing systems theory and resources-based view, Nevo and Wade (2010) propose a conceptual model of IT business value generation, indicating that the VRIN resource for sustainable competitive advantage can be developed when the synergy effect of IT asset and organizational source, in conjunction with enabling conditions (i.e., integration effort and compatibility) occurs in an organization. This synergy effect of IT asset and organizational source has yet to be examined. As these studies explain conceptually how firms achieve superior business value with the development of organizational capabilities and the aid of IT, further attention to empirically validate the interconnected dynamics in IT business value generation process support by various IT and organizational elements.

We took on this challenge by initially confirming that IT business value generation indeed depends on the joint effects of IT capability, complementary organizational resources, and organizational capabilities through our fsQCA analysis. This advances our understanding of "IT business value generation process as grey box" (Schryen, 2013, p.149) by explicating the complex causality among IT capabilities, complementary organizational resources, and organizational capabilities in the business value of IT generation process. Our findings not only reveal the synergy effect of IT capabilities (e.g., big data analytics capabilities) and human IT as a supportive role (e.g., analytics personnel's technical skills) in achieving business value, but also show IT is not in isolation from other elements (organizational resources and capabilities play a peripheral role to drive business value). In our research context, fsQCA results provide the "recipes" for achieving quality of care by considering the presence or absence of the "ingredients" (elements). Specifically, our findings explain how readmission rate and patient satisfaction can be improved in healthcare organizations with the combination effects of big data analytics, particularly in facilitating analytical and decision support capabilities with peripheral support from the organizational elements such as dynamic capabilities.

Our fsQCA application also makes a methodological contribution to IS research in general. Extending the theoretical perspective from strategic alignment between IT and business to co-evolution, some IS strategy studies have suggested that the key to successful health information technologies (HIT) implementation is to orchestrate complex and dynamic interactions between organizational capabilities and HIT during the business process (Agarwal et al., 2010; Goh, Gao, & Agarwal, 2011; Novak et al., 2012). Although these studies have noted the systemic notion of co-evolution among individual elements for IS success, examining the effect of co-evolution with conventional correlation-based linear methods (e.g., two-way correlations, testing moderator/mediator effect) does not allow a holistic view and not suitable for capturing the non-linear interdependent interactions among these elements.

As El Sawy et al. (2010) suggest that fsQCA is a powerful technique to understand the IS phenomena, for example digital ecodynamics can be developed by the holistic confluence among environmental turbulence, dynamic capabilities, and IT systems. Only few studies to date have employed fsQCA to address IT related issues such as IT adoption (Ceric & Krivokapic-Skoko, 2016) and IS behavioral intention issues (Liu, Mezei, Kostakos, & Li, 2015). To the best of our knowledge, this study is among the first to introduce fsQCA into the business value of IT research and use it to investigate the complex causality and diversity in IT business value generation process.

Unlike traditional correlation-based methods such as regression, fsQCA does not seek to discover relationships in which an incremental change in an independent variable (condition) leads to an incremental change in a dependent variable (outcome). Instead, this method is best suited for investigating an interconnected dynamics of a complex system like IT capability in which the impact of one element on the outcome of interest is dependent on other elements and a little change in one element can trigger changes in other elements and eventually change the whole organizational and technological structures and thus performance.

Through fsQCA our study provides “solutions” to healthcare practitioners as how to leverage big data analytics for better quality of care. By comparing the similarities and differences between multiple equifinal configurations, we extract patterns or pathways that healthcare practitioners can follow under their individual organizational situation of their culture, structure, process, and capabilities. Healthcare organization managers can follow a certain recipe to achieve high healthcare quality and to avoid the pitfalls of misplaced big data analytics investments.

Limitation and Future Research

While we believe that fsQCA method can contribute to business value of IT research, we acknowledge that this method has limitations. Firstly, FsQCA depends on prior knowledge or literature for the selection of the conditions and the outcome, and to simplify configurations (Liu et al., 2015). The configurations are sensitive to the range of conditions included – adding or removing conditions could result in different solutions (Ordanini, Parasuraman, & Rubera, 2014). Although the selection of the conditions in our analysis was built on the business value of IT generation framework provided by Melville et al. (2004) and was informed by a comprehensive review of the extant literature on big data analytics, the conditions we chose are mainly from the exploratory studies or case studies without empirical support. Some of care quality drivers could have been overlooked or overestimated. To address this concern, future research could potentially identify other prudent conditions by incorporating a mixed method research design (e.g., qualitative Delphi approach and content analysis).

Secondly, there are limitations and advantages of our dataset. The limitation is that we had a small sample size for our matchup dataset. Although fsQCA is sensitive to case selection (Liu et al., 2015), it allows analyzing small to medium of cases (e.g., 10 to 50) which traditional regression based methods may not be capable to solve (Ragin, 2008). We also took a step toward realism by using actual measures (e.g., average excess readmission ratio) from CMS database for assessing the care quality outcomes rather than scaled self-reporting performance. Doing so has the benefit of making more accurate interpretation for each configuration.

Thirdly, as big data analytics is still in incipient in the IS field, there is no validated measurement items for big data analytics capability. We determined the constructs and underlying items by refining statements iteratively from our review of academic research. However, the sample size used for validating the big data analytics capability scale was relatively small, although the representativeness of our sample may overcome the sample size issue to some extent. All of the participants in this study served as senior IT executives and were knowledgeable enough to able to provide strategic overviews of the big data analytics implementation in their healthcare organizations. Future research should carefully take further steps for scale development to minimize the potential bias.

Conclusion

Existing research primarily explores the key factors for the success of big data analytics implementation through traditional linear regression and correlation analysis. However, this study suggests that such regression-based methods may not allow a fully understanding of big data analytics implementation. Applying the configuration view and fsQCA that allows us to examine the systemic, equifinal, and discontinuous interactions among big data analytics elements and other related organizational elements, it helps to discover not only single drivers, but also sets of conditions that determine big data analytics' contribution to business value.

Findings of this study advance our understanding of how big data analytics-enabled IT capabilities combine with other organizational elements to achieve business value in health care. Most importantly, we offer evidence that different solutions leading to the same outcomes from the effective use of IT and other organizational elements do exist. This shows that fsQCA is a good analysis tool for business value of IT research and can offer new insights in understanding the generation of IT business value. Therefore, as the use of fsQCA is still at its infancy in most business domain, we call for more substantive discussions to ascertain the potential of applying fsQCA for business value of IT research.

Appendix A. Prior Literature Related to Big Data Analytics Success Model

Theory bases for assessing business value	Articles	Findings	Factors and pathways leading to business value of big data analytics
Variance theories	Seddon et al. (2012)	Developed long-term and short-term big data analytics models to identify critical factors leading to organizational benefits	(1) Long-term model: Analytic leadership, enterprise-wide analytics orientation, well-chosen targets, and evidence-based decision making (2) Short-term model: functional fit of BA tools, readily available high-quality data, analytical people, overcoming organizational inertia
	Knabke & Olbrich (2015)	Investigated how current business trends affect data warehouse-based business intelligence (BI) and dynamic BI capabilities, and in turn lead to support decision making	Dynamic BI capabilities, including organization & governance, business processes, change management & change behavior, people & culture, technology & infrastructure, and IS portfolio & IS architecture
	Trkman et al. (2010)	Examined the relationship between analytical capabilities in the supply chain management and its performance using information system support and business process orientation as moderators	Analytics of plan capability, analytics of source capability, Analytics of make capability, Analytics of delivery capability
	Cao et al. (2015)	Developed a model linking big data analytics to organizational decision-making effectiveness	The extent to which big data analytics is being used, data-driven environment, and information processing capability
	Wixom et al. (2013)	Explored two key factors and their underlying dimensions for maximizing big data analytics value in a fashion retailer case	Speed to insight (driven by automation, business requirements, and reuse), pervasive use (driven by graphics, mobility, user engagement)
	Chasalow & Baker (2015)	Tested a model that account for the nature of BI dynamic capabilities on business	BI dynamic capabilities were affected by organizational process(sensing, learning,

		process performance	coordinating, and integrating), firm IT assets (IT infrastructure and information repositories), and firm history (IT dynamic capability and information dynamic capability), which in turn lead to business process performance
	Ghasemaghaei et al. (2015)	Explore the role of fit between different organizational resources associated with big data use as key enablers of organizational agility and performance	Perceived fit between (1) big data tools and data; (2) big data tools and analytics people; (3) tasks and big data tools; and (4) task and data
	Someh & Chanks (2015)	This study proposed that big data analytics capability creates informational benefits in customer relations by using direct effect and indirect effect of higher-order analytics CRM capability	Big data analytics capability and analytics CRM capability
	Wang et al. (2015)	Identity the big data analytics capabilities from 26 published case studies and formulate more effective big data based strategies	Big data analytics capabilities, including traceability, unstructured data analytical capability, analytical capability for patterns of care, predictive capability, and decision support capability
Process theories	Tamm et al. (2013)	Explored the two types of BA users such as analytics professionals (APs) and analytics end-users (AEUs) and identified how these roles lead to three pathways to value from big data analytics	Pathway 1: Aps from third parties provide advisory services (insights) → AEUs decisions → Competitive actions → Organizational benefits Pathway 2: Aps create and improve analytics tools and embed analytic capabilities in operational systems→ AEUs decisions → Competitive actions → Organizational benefits Pathway 3: AUEs' analytics capabilities → Insights → Decisions → Competitive actions → Organizational capabilities

	Shanks & Bekmanedova (2012)	Evident in a longitudinal case study, they explained how big data analytics systems can create values by big data analytics-enabled organizational capabilities and dynamic capabilities	Big data analytics-enabled organizational capabilities (From T1 to T2)→organizational learning→dynamic capabilities (search and select and asset orchestration)→achieved business benefits
	Gao et al. (2015)	Firstly identified the critical success factors (CSF) from published case studies and then assigned theses success factors to a process model for big data projects	Business phase (CSFs such as identifiable business value and manageable project scope)→data phase (CSFs such as combine different data sets and high data quality)→analysis phase (CSFs such as innovative analysis tools and visualization)→implementation phase (CSFs such as information strategy for big data and interpretation of analytical results)→measurement phase (CSFs such as clear project goal with deadline and measurable outcome)

Appendix B. Skill Sets for Analytical Personnel across five versions

Chiang et al. (2012)	Wixom et al. (2014)	Mamonov et al. (2014)	Wilder and Ozgur (2015)	Cegielski and Jones-Farmer (2016)
• Analytical skills (e.g., data mining, deviational analysis and anomaly detection, geospatial and temporal analysis) • IT skills (e.g., relational databases, data warehouse, Hadoop, MapReduce, unstructured data management) • Business knowledge and communication skills (e.g., understanding business issues listening to what the business needs)	• Communication skills • SQL and Query skills • Basic analytics • Data management • Business requirement • Data integration • Business knowledge • Reporting (OLAP) skills • Research methods • Visualization • Advanced analytics • Data and text mining • Programing • Emerging topics • No SQL skills	• Applied statistics (e.g., distributions, sampling statistical inference, linear regression) • Technical skills (e.g., data storage/extraction, SQL, Data warehousing, Hadoop) • Analytical software (e.g., excel, SAS, R, Tableau) • Soft skills (e.g., communication & presentation, teamwork)	• 1st skill level - data scientist (e.g., a solid foundation in computer science and mathematics) • 2nd skill level – data specialists (e.g., understand how data is managed) • 3rd skill level – business analyst (e.g., identify and exploit business opportunities, frame business problems and interpret the results)	• Technical skills (e.g., ability to integrate analyses from multiple sources into a business solution, ability to use data visualization/graphical tools to interpret data, and ability to frame a business problem or question analytically) • Business skills (e.g., independent learner, organizational skills, industry specific knowledge)

Appendix C. Instrument

AUBURN
UNIVERSITY

RAYMOND J. HARBERT
COLLEGE OF BUSINESS
DEPARTMENT OF AVIATION & SUPPLY CHAIN MANAGEMENT

INFORMATION LETTER

"Exploring Configurations for Maximizing Value from Big data Analytics in Healthcare."

You are invited to participate in a research study to explore the configurations for maximizing business value from big data analytics for healthcare organizations. The study is being conducted by Yichuan Wang, doctoral candidate, under the direction of Dr. Terry A. Byrd, Professor of Information Systems the Department of Aviation and Supply Chain Management in the Auburn University College of Business. You were selected as a possible participant in this study because you are currently employed in an IT-related position and you are of 19 years of age or older.

What will be involved if you are participate? Your participation in this study is completely voluntary. If you decide to participate in this study, you will be asked to provide a suggestion regarding the use of big data analytics for your healthcare organization. We ask that you complete the study at home, at your convenience. Your total time commitment will be approximately 10-15 minutes.

Are there any ricks or discomforts? There are no risks or discomfort associated with participation in the study. Keep in mind that you can withdraw from this study at any time.

Will you receive compensation for participating? There is no compensation for participating in this study.

Are there any cost? There are no anticipated costs associated with participation in this study.

If you change your mind about participating, you may withdraw from this study at any time. Your participation is completely voluntary.

All the data collected as part of this study will be completely anonymous. We will protect your privacy and the data you provide by not collecting any personally identifiable information from you. The data collected in this study may be used in a publication in an academic journal and/or presentation at a professional conference.

If you have any question about this study, please contact Yichuan Wang at 3(18)278-4630 or yzw0037@auburn.edu, or contact Dr. Terry Byrd at (334) 844-6543 or byrdter@auburn.edu.

HAVING READ THE INFORMATION ABOVE, YOU MUST DECIDE IF YOU WANT TO PARTICIPATE IN THIS RESEARCH PROJECT. IF YOU DECIDE TO PARTICIPATE, PLEASE CLICK ON THE LINK BELOW.
YOU MAY PRINT A COPY OF THIS LETTER TO KEEP.

Big data Analytics Capabilities

Please rate the effectiveness by which your hospital uses the following big data analytics functionalities in the business process

Traceability (Newly developed)

1. Integrate seamlessly clinical data across multiple departments in near real time or real time
2. Track medical events based on the rules that built on hospital claims
3. Search clinical databases for all data related to patients

Analytical capability (Newly developed)

1. Analyze large amounts of clinical data to understand the past and current state for specific target variables
2. Explore the causes of medical events from clinical data
3. Support real-time processing of multiple clinical data streams

Decision Support capability (Newly developed)

1. Generate clinical summary in real time or near real time and present in visual dashboards
2. Provide system outputs for role-based decision-making

Predictive analytics capability (Newly developed)

1. Discover patterns among specific variables of interest across departments
2. Analyze data from different sources and use the results to predict future trends

3. Provide actionable insights from clinical data in a format readily understood by healthcare providers

Analytics personnel skills

Please evaluate whether the data analysts in your hospital have the following analytics personnel skills

Technical skills (Cegielski & Jones-Farmer, 2016; Wixom et al., 2014)

1. Ability to integrate analyses from multiple sources into a business solution
2. Ability to use data visualization/graphical tools to interpret data
3. Ability to frame a business problem or question analytically
4. Ability to solve pre-framed business problems or questions analytically

Business skills (Cegielski & Jones-Farmer, 2016; Wixom et al., 2014)

1. Ability to be an independent learner
2. Organizational skills
3. Healthcare knowledge

Evidence-based decision making culture (Kiron et al., 2012; Kiron & Shockely, 2011; Popovič et al., 2012)

The extent to which you agree or disagree with the following statements about you company's culture

1. Our hospital usually uses evidence-based insights for the creation of new service/product.
2. Our hospital is open to new ideas and approaches that challenge current or future projects on the basis of new insights.
3. Our hospital allows incorporating available information within any decision-making process.

Data governance (Khatri & Brown, 2010)

Your hospital has provided a guideline and established the policies and rules on the following the core components of data governance that guide our big data analytics activities

1. Data principle (clarifying the role of data as an asset)
2. Data quality (establishing the requirements of intended use of data)
3. Metadata (establishing the semantics of data so that it is interpretable by the users)
4. Data access (specifying access requirement of data)
5. Data lifecycle (determining the definition, production, retention and retirement of data)

Planned dynamic capabilities (Pavlou & El Sawy, 2010)

Please rate the effectiveness by which your hospital reconfigures its operational capabilities in the healthcare services to address rapidly-changing environments

1. Our hospital frequently generates, disseminate, and respond to market intelligence about customer needs.
2. Our hospital has adequate routines to acquire, assimilate, transform, and exploit existing resources to generate new knowledge.
3. Our hospital is effective in managing dependencies among resources and tasks to synchronize activities.
4. Our hospital effectively integrates disparate employees' inputs through heedful contribution, representation, and interrelation into our group.

Improvisational capabilities (Moorman & Miner, 1998; Pavlou & El Sawy, 2010)

Please rate the effectiveness by which your hospital spontaneously reconfigures its operational capabilities in the healthcare service in novel environmental situations

1. Our hospital is successful in figuring out our actions as we go along.

2. Our hospital effectively improvises in carrying out our activities.

3. Our hospital could spontaneously readjust our activities according to competitive environments.

Appendix D. Item Loadings and Cross Loadings

	TRA	ANA	DSC	PRE	TS	BS	CUL	DG	DYN	IM
TRA1	**.801**	-.096	.091	.020	.167	-.118	.057	.033	.273	.027
TRA2	**.782**	.180	.173	-.088	.268	.072	.089	-.070	.193	-.104
TRA3	**.886**	.028	-.010	.097	.124	.060	.086	-.064	.036	-.009
ANA1	.077	**.873**	.103	.094	-.004	-.047	.101	-.078	-.046	.258
ANA2	.021	**.913**	-.024	.118	-.089	.080	.032	-.107	-.038	.121
ANA3	-.023	**.802**	.135	.094	-.245	-.053	.034	-.025	.105	.202
DSC1	.045	.092	**.907**	.074	-.113	.069	.047	-.152	.164	-.004
DSC2	.181	.085	**.843**	.168	-.205	.100	.073	-.129	-.041	.170
PRE1	.098	.072	.150	**.867**	.099	.090	.093	-.090	-.005	.067
PRE2	-.020	.184	-.004	**.832**	.269	-.019	-.009	.034	.014	.059
PRE3	-.017	.048	.073	**.836**	.144	.196	-.072	-.048	.005	.053
TS1	.065	-.082	-.123	.192	**.833**	.094	-.057	-.010	.179	.075
TS2	.127	-.100	-.035	.060	**.865**	.089	-.037	.090	.162	-.008
TS3	.188	-.131	-.132	.201	**.792**	.262	-.016	-.026	.112	-.016
TS4	.208	-.054	-.051	.149	**.804**	-.011	-.061	.081	.091	-.229
BS1	.013	.101	.266	.060	.156	**.731**	.271	.058	-.142	-.018
BS2	.015	-.102	-.042	-.008	.133	**.853**	-.069	-.016	.027	.056
BS3	-.015	.031	.032	.246	.063	**.828**	.069	.155	-.060	.022
CUL1	.128	-.006	-.015	-.151	-.074	-.040	**.922**	.003	-.063	.030
CUL2	.054	.154	.084	.057	-.045	.122	**.833**	-.156	-.096	.077
CUL3	.038	.014	.060	.130	-.029	.111	**.778**	-.292	-.124	.206
DG1	-.157	-.256	-.115	-.028	.172	.040	-.012	**.812**	.087	.052
DG2	.031	-.267	-.281	-.026	.056	.030	.002	**.765**	-.003	-.069
DG3	-.062	.039	-.014	.077	-.039	.037	-.206	**.804**	.044	.059
DG4	.034	.069	.028	-.124	.086	.110	-.014	**.650**	-.228	.041
DG5	.029	.053	-.009	-.019	-.104	-.025	-.155	**.806**	-.009	-.180
DYN1	.091	-.011	-.093	-.054	.161	-.034	-.282	.032	**.768**	-.114
DYN2	.189	.000	.023	.034	.073	-.070	-.041	-.058	**.883**	.054
DYN3	.128	-.090	.035	.084	.110	-.089	-.046	.008	**.915**	.067
DYN4	.042	.189	.274	-.100	.282	.093	.043	-.118	**.715**	-.211
IM1	.020	.245	.228	.072	-.067	.024	.174	-.001	-.077	**.832**
IM2	-.015	.152	-.008	-.074	.055	.046	.046	-.079	.045	**.898**
IM3	-.070	.174	-.039	.217	-.142	.004	.079	.011	-.078	**.827**

Note: TRA = traceability; ANA = analytical capability; DSC = decision support capability; PRE = predictive capability; TS = personnel's technical skills; BS = personnel's business skills; CUL = evidence-based decision making culture; DG = data governance; DYN = planned dynamic capabilities; IM = improvisational capabilities. Bold numbers indicate item loadings on the assigned constructs.

References

Agarwal, R., Gao, G., DesRoches, C., & Jha, A. K. (2010). Research commentary-The digital transformation of healthcare: current status and the road ahead. *Information Systems Research*, 21(4), 796-809.

Agha, L. (2014). The effects of health information technology on the costs and quality of medical care. *Journal of Health Economics*, 34, 19-30.

Banker, R. D., Bardhan, I.R., Chang, H., & Lin, S. (2006). Plant information system, manufacturing capabilities, and plant performance. *MIS Quarterly*, 30(2), 315-337.

Barclay, D., Higgins, C., & Thompson, R. (1995). The partial least squares (PLS) approach to causal modeling: Personal computer adoption and use as an illustration. *Technology Studies*, 2(2), 285-309.

Bardhan, I. R., & Thouin, M. F. (2013). Health information technology and its impact on the quality and cost of healthcare delivery. *Decision Support Systems*, 55(2), 438-449.

Bardhan, I., Oh, J. H., Zheng, Z., & Kirksey, K. (2015). Predictive analytics for readmission of patients with congestive heart failure. *Information Systems Research*, 26(1), 19-39.

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

Barney, J., Wright, M., & Ketchen, D. J. (2001). The resource-based view of the firm: Ten years after 1991. *Journal of Management*, 27(6), 625-641.

Bharadwaj, A. S. (2000). A resource-based perspective on information technology capability and firm performance: An empirical investigation. *MIS Quarterly*, 24(1), 169-196.

Bradley, R. V., Pratt, R. M., Byrd, T. A., Outlay, C. N., & Wynn Jr, D. E. (2012). Enterprise architecture, IT effectiveness and the mediating role of IT alignment in US hospitals. *Information Systems Journal*, 22(2), 97-127.

Brady, H., & Collier, D. (2010). *Rethinking Social Inquiry: Diverse Tools, Shared Standards* (Second ed.): Rowman & Littlefield Publishers.

Brewer, M. B., Campbell, D. T., & Crano, W. D. (1970). Testing a single-factor model as an alternative to the misuse of partial correlations in hypothesis-testing research. *Sociometry*, 33(1), 1-11.

Cao, G., Duan, Y., & Li, G. (2015). Linking business analytics to decision making effectiveness: A path model analysis. *IEEE Transactions on Engineering Management*, 62(3), 384-395.

Ceric, A., & Krivokapic-Skoko, B. (2016). Applying QCA and Cross-impact Analysis to the Study on ICT Adoption and Use by Croatian SMEs. In Complexity in Entrepreneurship, Innovation and Technology Research (pp. 349-370). Springer International Publishing.

Chasalow, L. C., & Baker, E. W. (2015). Factors contributing to business intelligence success: The impact of dynamic capabilities. In *Proceeding of Twenty-first Americas Conference on Information Systems*, Puerto Rico, USA.

Chiang, R. H. L., Goes, P., & Stohr, E. A. (2012). Business intelligence and analytics education, and program development: A unique opportunity for the information systems discipline. *ACM Transactions Management Information Systems*, 3(3), 12.

Chin, W. W. (1998). *The Partial Least Squares Approach to Structural Equation Modeling*. In Modern Methods for Business Research, G. A. Marcoulides (ed.), Mahwah, NJ: Lawrence Erlbaum Associates, Inc., 295-336.

Centers for Medicare & Medicaid Services (CMS). (2014). *System Requirements Specification Hospital Compare Downloadable Database Data Dictionary*. Centers for Medicare & Medicaid Services.

Collier, D., & Gerring, J. (2009). *Concepts and Method in Social Science: The Tradition of Giovanni Sartori*. New York and London: Routledge.

Collis, D. J. (1994). Research note: How valuable are organizational capabilities. *Strategic Management Journal*, 15(8), 143-152.

Cress, D. M., & Snow, D. A. (2000). The outcomes of homeless mobilization: The influence of organization, disruption, political mediation, and framing. *American Journal of Sociology*, 105(4), 1063-1104.

Crilly, D. (2011). Predicting Stakeholder Orientation in the Multinational Enterprise: A Mid-Range Theory. *Journal of International Business Studies*, 42(5), 694-717.

Davenport, T. H. (2006). Competing on analytics. *Harvard Business Review*, 84 (1), 98-107.

Davenport, T. H., & Harris, J. G. (2007). Competing on analytics: The new science of winning. Harvard Business Press.

Davenport, T. H., & Patil, D. J. (2012). Data scientist: The sexiest job of the 21st century. *Harvard Business Review*, 70-76.

Davenport, T. H., Harris, J. S., & Morison, R. (2010). *Analytics at Work*, Cambridge, MA: Harvard Business School Press.

El Sawy, O. A. Malhotra, A. Park, Y., & Pavlou, P. A. (2010). Seeking the configurations of digital ecodynamics: It takes three to tango. *Information Systems Research*, 21(4), 835-848.

El Sawy, O. A., & Pavlou, P. A. (2008). IT-enabled business capabilities for turbulent environments. *MIS Quarterly Executive*, 7(3), 139-150.

Ennen, E., & Richter, A. (2010). The whole is more than the sum of its parts—or is it? A review of the empirical literature on complementarities in organizations. *Journal of Management*, 36(1), 207-233.

Fichman, R. G. (2004). Going beyond the dominant paradigm for information technology innovation research: Emerging concepts and methods. *Journal of the Association for Information Systems*, 5(8), 314-355.

Fichman, R. G., Nambisan, S., & Halpern, M. (2014). Configurational thinking and value creation from digital innovation: The case of product lifecycle management. In Innovation and IT in an International Context, F. Rowe and D. Te'eni (eds.), London: Palgrave Macmillan.

Fiss, P. C. (2007). A set-theoretic approach to organizational configurations. *Academy of Management Review*, 32(4), 1180-1198.

Fiss, P. C., Cambré, B., & Marx, A. (2013). Configurational theory and methods in organizational research (Vol. 38). Emerald Group Publishing.

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

Gao, J., Koronios, A., & Selle, S. (2015).Towards a process view on critical success factors in big data analytics projects. In *Proceeding of Twenty-first Americas Conference on Information Systems*, Puerto Rico, USA.

Ghasemaghaei, M., Hassanein, K., & Turel, O. (2015). Impacts of big data analytics on organizations: A resource fit perspective. In *Proceeding of Twenty-first Americas Conference on Information Systems*, Puerto Rico, USA.

Gillon, K., Aral, S., Lin, C. Y., Mithas, S., & Zozulia, M. (2014). Business analytics: radical shift or incremental change? *Communications of the Association for Information Systems*, 34, 287-296.

Grigoroudis, E., Orfanoudaki, E., & Zopounidis, C. (2012). Strategic performance measurement in a healthcare organisation: A multiple criteria approach based on balanced scorecard. *Omega*, 40(1), 104-119.

Groves, P., Kayyali, B., Knott, D., & Kuiken, S.V. (2013). *The "Big Data" Revolution in Healthcare: Accelerating Value and Innovation*. McKinsey & Company.

Henfridsson, O., & Bygstad, B. (2013). The generative mechanisms of digital infrastructure evolution. *MIS Quarterly*, 37(3), 907-931.

IBM. (2012). *Understanding Holistic Database Security: 8 Steps to Successfully Securing Enterprise Data Sources*, IBM Corporation.

Jagadish, H.V., Gehrke, J., Labrinidis, A., Papakonstantinou, Y., Patel, J.M., Ramakrishnan, R., & Shahabi, C. (2014). Big data and its technical challenges. *Communications of the ACM* 57(7), 86-94.

Kettinger, W., Zhang, C., & Marchand, D. A. (2011). CIO and business executive leadership approaches to establishing company-wide information orientation. *MIS Quarterly Executive*, 10(4), 157-174.

Khatri, V., & Brown, C. V. (2010). Designing data governance. *Communications of the ACM*, 53(1), 148-152.

Kim, G., Shin, B., Kim, K. K., & Lee, H. G. (2011). IT capabilities, process-oriented dynamic capabilities, and firm financial performance. *Journal of the Association for Information Systems*, 12(7), 487-517.

Kiron, D., & Shockley, R. (2011). Creating business value with analytics. *MIT Sloan Management Review*, 53(1), 57-63.

Kiron, D., Prentice, P. K., & Ferguson, R. B. (2012). Innovating with analytics. *MIT Sloan Management Review*, 54(1), 47-51.

Knabke, T., & Olbrich, S. (2015). Exploring the future shape of business intelligence: Mapping dynamic capabilities of information systems to business intelligence agility. In *Proceeding of Twenty-first Americas Conference on Information Systems*, Puerto Rico, USA.

Kooper, M. N., Maes, R., & Lindgreen, E. R. (2011). On the governance of information: Introducing a new concept of governance to support the management of information. *International Journal of Information Management*, 31(3), 195-200.

LaValle, S., Lesser, E., Shockley, R., Hopkins, M. S., & Kruschwitz, N. (2011). Big data, analytics and the path from insights to value. *MIT Sloan Management Review*, 52(2), 21-31.

Lee, Y., Madnick, S., Wang, R., Wang, F., & Zhang, H. (2014). A cubic framework for the chief data officer: Succeeding in a world of big data. *MIS Quarterly Executive*, 13(1), 1-13.

Legewie, N. (2013) An Introduction to Applied Data Analysis with Qualitative Comparative Analysis. In *Forum Qualitative Sozialforschung/Forum: Qualitative Social Research*, 14(3), 15.

Lindell, M. K., & Whitney, D. J. (2001). Accounting for common method variance in cross-sectional research designs. *Journal of Applied Psychology*, 86(1), 114-121.

Liu, Y., Mezei, J., Kostakos, V., & Li, H. (2015). Applying configurational analysis to IS behavioural research: a methodological alternative for modelling combinatorial complexities. *Information Systems Journal*, DOI: 10.1111/isj.12094.

Loshin, D. (2010). *Master Data Management*. Morgan Kaufmann.

Luo, J., Fan, M., & Zhang, H. (2012). Information technology and organizational capabilities: A longitudinal study of the apparel industry. *Decision Support Systems*, 53(1), 186-194.

Mahoney, J. (2010). After KKV: The new methodology of qualitative research. *World Politics, 62*(1), 120-147.

Mamonov, S., Misra, R., Jain, R. (2015). Business analytics in practice and in education: A competency-based perspective. *Information Systems Education Journal*, 13(1), 4-13.

March, J. G. (1991). Exploration and exploitation in organizational learning. *Organization Science*, 2(1), 71-87.

Markus, M. L., & Robey, D. (1988). Information technology and organizational change: causal structure in theory and research. *Management Science*, 34(5), 583-598.

Marx, A. (2010). Crisp-set qualitative comparative analysis (csQCA) and model specification: Benchmarks for future csQCA applications. *International Journal of Multiple Research Approaches*, 4(2), 138-158.

McAfee, A., & Brynjolfsson, E. (2012). Big data. The management revolution. *Harvard Business Review*, 90(10), 59-68.

Melville, N., Kraemer, K., & Gurbaxani, V. (2004). Review: information technology and organizational performance: An integrative model of IT business value. *MIS Quarterly*, 28(2), 283-322.

Menon, N. M., & Kohli, R. (2013). Blunting Damocles' sword: A longitudinal model of healthcare IT impact on malpractice insurance premium and quality of patient care. *Information Systems Research*, 24(4), 918-932.

Meyer, A. D., Tsui, A. S., & Hinings, C. R. (1993). Configurational approaches to organizational analysis. *Academy of Management Journal*, 36(6), 1175-1195.

Mikalef, P., Pateli, A., Batenburg, R. S., & Wetering, R. V. D. (2015). Purchasing alignment under multiple contingencies: a configuration theory approach. *Industrial Management & Data Systems*, 115(4), 625-645.

Milgrom, P., & Roberts, J. (1995). Complementarities and fit strategy, structure, and organizational change in manufacturing. *Journal of Accounting and Economics*, 19(2), 179-208.

Moorman, C., & Miner, A. S. (1998). Organizational improvisation and organizational memory. *Academy of management Review*, 23(4), 698-723.

Mueller, B., Viering, G., Legner, C., & Riempp, G. (2010). Understanding the economic potential of service-oriented architecture. *Journal of Management Information Systems*, 26(4), 145-180.

Needle, D. (2010). *Business in Context: An Introduction to Business and its Environment*. Cengage Learning EMEA.

Nevo, S., & Wade, M. R. (2010). The formation and value of IT-enabled resources: antecedents and consequences of synergistic relationships. *MIS Quarterly*, 34(1), 163-183.

Novak, L., Brooks, J., Gadd, C., Anders, S., & Lorenzi, N. (2012). Mediating the intersections of organizational routines during the introduction of a health IT system. *European Journal of Information Systems*, 21(5), 552-569.

Ordanini, A., Parasuraman, A., & Rubera, G. (2014). When the recipe is more important than the ingredients a Qualitative Comparative Analysis (QCA) of service innovation configurations. *Journal of Service Research*, 17(2), 134-149.

Park, Y., & El Sawy, O. A. (2013). The value of configurational approaches for studying digital business strategy. *Research in the Sociology of Organizations*, 38, 205-224.

Pavlou, P. A., & El Sawy, O. A. (2006). From IT leveraging competence to competitive advantage in turbulent environments: The case of new product development. *Information Systems Research*, 17(3), 198-227.

Pavlou, P. A., & El Sawy, O. A. (2010). The "third hand": IT-enabled competitive advantage in turbulence through improvisational capabilities. *Information Systems Research*, 21(3), 443-471.

Pavlou, P. A., Liang, H., & Xue, Y. (2007). Understanding and mitigating uncertainty in online environments: a principal-agent perspective. *MIS Quarterly*, 31(1), 105-136.

Piccoli, G., & Ives, B. (2005). Review: IT-dependent strategic initiatives and sustained competitive advantage: a review and synthesis of the literature. *MIS Quarterly*, 29(4), 747-776.

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

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: a critical review of the literature and recommended remedies. *Journal of Applied Psychology*, 88(5), 879-903.

Popovič, A., Hackney, R., Coelho, P. S., & Jaklič, J. (2012). Towards business intelligence systems success: Effects of maturity and culture on analytical decision making. *Decision Support Systems*, 54(1), 729-739.

Pye, J., Rai, A., & Baird, A. (2014). Healthcare information technology in U.S. hospital: how much, how fast? In *Proceeding of Thirty Fifth International Conference on Information Systems*, Auckland, New Zealand.

Raghupathi, W., & Raghupathi, V. (2014). Big data analytics in healthcare: Promise and potential. *Health Information Science and Systems*, 2(1), 1-10.

Ragin, C. C. (1987). *The Comparative Method: Moving Beyond Qualitative and Quantitative Strategies*. Berkeley: University of California Press.

Ragin, C. C. (2000). *Fuzzy-Set Social Science*. Chicago: University of Chicago Press.

Ragin, C. C., & Fiss, P. C. (2008). Net effects analysis versus configurational analysis: An empirical demonstration. *Redesigning social inquiry: Fuzzy sets and beyond*, 190-212.

Ragin, C. C., Kriss A. Drass, & Sean Davey. (2006). Fuzzy-Set/Qualitative Comparative Analysis 2.0. Tucson: Department of Sociology, University of Arizona.

Ragin, C.C. (2008a). *Redesigning Social Inquiry: Fuzzy Sets and Beyond*, University of Chicago Press: Chicago and London

Ragin, C.C. (2008b). User's Guide to Fuzzy-Set/Qualitative Comparative Analysis.

Rai, A., Patnayakuni, R., & Seth, N. (2006). Firm performance impacts of digitally enabled supply chain integration capabilities. *MIS Quarterly, 30*(2), 225-246.

Ravasi, D., & Schultz, M. (2006). Responding to organizational identity threats: Exploring the role of organizational culture. *Academy of Management Journal*, 49(3), 433-458.

Rihoux, B., & Ragin, C. C. (2009). *Configurational Comparative Methods: Qualitative Comparative Analysis (QCA) and Related Techniques*, Thousand Oaks, CA: SAGE Publications.

Ringle, C. M., Wende, S., & Will, A. (2005). SmartPLS 2.0 (M3). Hamburg: SmartPLS. Retrieved from http://www.smartpls.com.

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

Sambamurthy, V., Bharadwaj, A., & Grover, V. (2003). Shaping agility through digital options: Reconceptualizing the role of information technology in contemporary firms. *MIS Quarterly*, 237-263.

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

Schneeweiss, S. (2014). Learning from big health care data. *The New England Journal of Medicine*, 370(23), 2161-2163.

Schneider, C. Q., & Wagemann, C. (2012). *Set-theoretic Methods for the Social Sciences: A Guide to Qualitative Comparative Analysis*. Cambridge University Press.

Schryen, G. (2013). Revisiting IS business value research: What we already know, what we still need to know, and how we can get there. *European Journal of Information Systems*, 22, 139-169.

Seddon, P. B., Constantinidis, D., & Dod, H. (2012). How does business analytics contribute to business value? In *Proceeding of the 33rd International Conference on Information Systems*, Orlando, Florida.

Shah, N.D., & Pathak, J. (2014). Why Health Care May Finally Be Ready for Big Data. Retrieved January 12, 2015 from Harvard Business Review: https://hbr.org/2014/12/why-health-care-may-finally-be-ready-for-big-data.

Shanks, G., & Bekmamedova, N. (2012). Achieving benefits with business analytics systems: an evolutionary process perspective. *Journal of Decision Systems*, 21(3), 231-244.

Sharma, R., Mithas, S., & Kankanhalli, A. (2014). Transforming decision-making processes: a research agenda for understanding the impact of business analytics on organisations. *European Journal of Information Systems*, 23(4), 433-441.

Someh, I. A., & Shanks, G. (2015). How business analytics systems provide benefits and contribute to firm performance? In *Proceeding of Twenty-Third European Conference on Information Systems (ECIS)*, Münster, Germany.

Tamm, T., Seddon, P., & Shanks, G. (2013). Pathways to value from business analytics. In *Proceeding of Thirty Fourth International Conference on Information Systems*, Milan, Italy.

Tanriverdi, H. (2005). Information technology relatedness, knowledge management capability, and performance of multibusiness firms. *MIS Quarterly*, 29(2), 311-334.

Tanriverdi, H. (2006). Performance effects of information technology synergies in multibusiness firms. *MIS Quarterly*, 30(1), 57-77.

Thiem, A. (2010). Set-relational fit and the formulation of transformational rules in fsQCA. COMPASSS Working Paper Series, 61, http://www.compasss.org/wpseries/Thiem2010.pdf

Thygeson, M., Peikes, D., & Zutshi, A. (2013). Fuzzy-Set Qualitative Comparative Analysis: A Configurational Comparative Method to Identify Multiple Pathways to Improve Patient-Centered Medical Home Models (Issue Brief). Mathematica Policy Research.

Treadwell, W. A. (1995). Fuzzy set theory movement in the social sciences. *Public Administration Review, 55*(1), 91-98.

Trkman, P., McCormack, K., De Oliveira, M. P. V., & Ladeira, M. B. (2010). The impact of business analytics on supply chain performance. *Decision Support Systems*, 49(3), 318-327.

Wang, Y., Kung, L., Ting, C., & Byrd, T. A. (2015). Beyond a technical perspective: Understanding big data capabilities in health care. In *Proceeding of the 48th Hawaii International Conference on System Sciences (HICSS)*, 3044-3053.

Wang, Y., Kung, L., Wang, W. Y. C., & Cegielski, C. G. (2014). Developing a big data-enabled transformation model in healthcare: A practice based view. In *Proceeding of Thirty-fifth International Conference on Information Systems*, Auckland, New Zealand.

Ward, M. J., Marsolo, K. A., & Froehle, C. M. (2014). Applications of business analytics in healthcare. *Business Horizons*, 57(5), 571-582.

Watson, H. J. (2014). Tutorial: Big data analytics: Concepts, technologies, and applications. *Communications of the Association for Information Systems*, 34, 1247-1268.

Wilder, C. R., & Ozgur, C. O. (2015). Business analytics curriculum for undergraduate majors. *INFORMS Transactions on Education*, 15(2), 180-187.

Winter, R., Gilbert, R., & Davis, J. R. (2013). *Big Data: What Does It Really Cost?* Cambridge, MA: Winter Corporation.

Wixom, B., Ariyachandra, T., Douglas, D., Goul, M., Gupta, B., Lyer, L., Kulkarni, U., Mooney, J. G., Phillips-Wren, G., & Turetken, O. (2014). The current state of business intelligence in academia: The arrival of big data. *Communications of the Association for Information Systems*, 34, 1-13.

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

Wu, I. L., & Hu, Y. P. (2012). Examining knowledge management enabled performance for hospital professionals: A dynamic capability view and the mediating role of process capability. *Journal of the Association for Information Systems*, 13(12), 976-999.

Xu, P., & Kim, J. (2014). Achieving dynamic capabilities with business intelligence. In *Proceeding of the 18th Pacific Asia Conference on Information Systems (PACIS 2014),* Chengdu, China.