The Use of Business Analytics Systems: An Empirical Investigation in Taiwan's Hospitals

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Research Paper

ABSTRACT

This paper aims to develop a research model to examine the mechanisms by which business analytics capabilities in healthcare units are shown to indirectly influence decision-making effectiveness through a mediating role of absorptive capacity. We employed a survey method to collect primary data from Taiwan's hospitals. 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 results found that healthcare units are likely to obtain valuable knowledge as they utilize the data interpretation tools effectively. Also, 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.

Keywords: Business analytics (BA), decision-marking effectiveness, absorptive capacity, organizational learning, knowledge-based view, health care

INTRODUCTION

Business analytics (BA) is increasingly advocated as an important strategic information technology (IT) investment for many organizations. BA systems encompass the various analytics techniques (e.g., descriptive analytics and predictive analytics) that can be used to support evidence-based decision-making and action-taking (Wang et al., 2015; Watson, 2014). Unlike other disruptive information technology (IT) innovation, BA is challenging healthcare entity to find a thoughtful, holistic approach to data, analysis and information management to facilitate timely and sound decisions making, and in turn to gain organization performance. Evidence shows that only 42 percent of healthcare organizations surveyed are adopting rigorous analytics approaches to support their decision-making process; only 16 percent of them have substantial experience using analytics across a broad range of functions (Cortada et al., 2012). Therefore, there is an urgent need to understand how healthcare organizations can improve their decision making processes from the use of BA systems.

Prior studies have explored the compelling pathways which linking from analytics use capabilities, through insights and decisions, to increased organizational benefits (e.g., Seddon et al., 2012; Sharma et al., 2014). Meanwhile, the elements of a successful business analytics implementation have been recognized for reshaping operational capabilities and generating economic value, including BA infrastructure and functionalities (e.g., Cao et al., 2015; Trkman et al., 2010; Wang et al., 2014; Wixom et al., 2013), analytical people (e.g., Seddon et al., 2012), data governance (LaValle et al., 2011; Seddon et al., 2012), information quality (Popovič et al., 2012), data-driven decision-marking culture (e.g., Kiron et al., 2012; Kiron and Shockely, 2011; Popovič et al., 2012; Ross, et al., 2013) and data-driven environment (Cao et al., 2015). Despite the critical elements and pathways leading to BA success have been discussed in the literature, there is a lack of strong empirical evidence of how organizational decision-making effectiveness can be influenced by the use of BA, especially in hospital settings.

To fill up this research gap, this study aims to explore the role of BA in achieving business value, specifically, to examine whether the effective use of business analytics tools enable healthcare organization to improve organizational benefit (i.e., decision-making effectiveness). Building on the resource-based view of IT and the IT capability literature (Bharadwaj, 2000; Santhanam and Hartono, 2003; Wang et al., 2013), we first introduce the multi-dimensional role of BA capabilities, which are shaped by a set of technological BA resources. The proposed BA capability is defined as the ability to effectively use the functionalities of BA systems to support the daily medical operations and activities. We argue that healthcare organizations rely on accurate evidence-based decisions to support medical practices, and are likely to be facilitated by BA capabilities.

An ongoing debate in the IS strategy literature is whether IT-enabled constructs specifically for IT architecture capabilities confer or facilitate competitive advantage directly or indirectly (Devaraj and Kohli, 2003; Wade and Hulland, 2004). Several studies have provided the evidence on the need for a mediating link between the use of BA and organizational performance (Cao et al., 2015; Popovič et al., 2012; Trkman et al., 2010). Due to the nature of high competitive intensity, healthcare organizations have to constantly seek and disseminate new knowledge to respond to industry regulations and market needs (Sharma et al., 2005). Organizations' ability to obtain and apply knowledge becomes critical since knowledge generated from the use of IT per se cannot generate value (Cohen and Levinthal 1990; Zahra and George 2002). Thus, extending this indirect view, this study proposes absorptive capacity as the missing link in the relationship between BA related constructs and decision-making effectiveness and argue that it plays an intermediary role in transforming knowledge obtained from the use of BA systems into the useful decision-making resource.

Put all together, this study sets out to answer the following research question:

Do business analytics capabilities improve decision-making effectiveness through a mediating role of absorptive capacity?

THEORETICAL BACKGROUD

Transforming decision-making processes through business analytics

Despite firms implement various decision support systems to pursue the delivery of information to decision-makers and to improve their decision-making effectiveness, the benefits have not had as much of an impact as anticipated (Sharma and 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 making timely decision to quickly respond to environmental turbulent and competitive markets in health care. To address this, several researchers suggest that the productivity and quality of decision-making can be improved with the aid of BA. Popovič et al. (2012) argue that a mature business intelligence system with strong analytical capabilities and data integration, along with the ability to use complex business intelligence system by knowledge workers can help obtain sufficient information for improving 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 affect information processing capability, which in turn results in enhancing 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 of IS success (Dickson et al., 1977; DeLone and McLean, 1992). It is defined as the users' perception towards decision-making satisfaction. Earlier works (e.g., Meador et al., 1984; Sanders and Courtney, 1985) were used decision-making effectiveness to measure the performance of decision support system. With respect to BA systems, decision-making effectiveness can be achieved by 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 analytics-based healthcare systems and individually linked to improve care of quality (Barjis et al., 2013; Foshay and Kuziemsky, 2014). Therefore, this study chose decision-making effectiveness to measure the performance of BA systems in the healthcare context. The following sections describe the roles of BA capabilities and analytical personnel, and absorptive capacity, which are proposed to influence decision-marking effectiveness.

Business Analytics Capacities

BA capability is a specific type of IT capability, 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 and Harris, 2007). We conceptualize BA capability by drawing on IT capability literature. IT capability literature generally takes resource-based view (Barney, 1991; Barney et al., 2001) to argue 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 (Santhanam and 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 been 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 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.

As Pavlou and El Sawy (2006) suggested, we identify the key dimensions of BA capability from the IT tools and functionalities of BA systems. To this end, the relevant academic literature (e.g., Raghupathi and Raghupathi, 2014; Ward et al., 2014), technology tutorial (Hu et al., 2014; Watson, 2014), and case descriptions regarding applying BA systems in healthcare were reviewed. Our starting point was Ward et al.'s (2014) proposed BA architectural framework in health care. This framework elucidates how decisions are made by four architectural layers that begin with data generation, through data extraction and data analysis, and end up with visualization and reporting, and lists the tools and functionalities are used in each architectural layer. With these dimensions in mind, we reviewed over 60 big data cases from diverse resources such as major IT vendors, academic journal databases, and healthcare institute reports for including, integrating, or dropping any dimension. This review affirmed Ward et al.'s framework, but it suggested the need to integrate data generation and data extraction under a single dimension – data aggregation. This is because that BA system typically uses the data warehousing tools to capture, aggregate and made various sources ready for processing (Raghupathi and Raghupathi, 2014). Summarizing this review, we propose three key dimensions of BA capability in healthcare: (1) effective use of data aggregation tools, (2) effective use of data analytics tools, and (3) effective use of data visualization and reporting tools, as described below. Table 1 summarizes what constitutes the effective use of these BA tools.

Table 1. Key constructs of BA capability

BA systems	Tools	Key functionalities	Effective use of BA systems
Data aggregation tools	• Middleware • Data warehouse • Transformation engines • 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	• Processing large amounts of unstructured	• Identify important business insights to

	• Statistical analysis • Predictive modeling • Social media analytics • Unstructured data analytics • Data/text mining	and semi-structured across massively parallel cluster of servers by Hadoop Map/Reduce • Real-time analysis by utilizing stream computing • In-database analytics for analyzing structure patient records • Social media analytics for analyzing web data	improve costly healthcare services such as unnecessary extra 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 trend from a large population
Data interpretation tools	• Data visualization systems • Real-time monitoring systems	• General summary of data • Visualization reporting • Real-time reporting	• Provide the systemic and comprehensive reporting to help recognize feasible opportunities for improvement • Support data visualization that enables users to easily interpret result. • 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 various 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 several data formats that can be read by the data analysis platform. As Raghupathi and Raghupathi (2014) stated, data will be intelligently aggregated by three key functionalities in data aggregation tools: acquisition, transformation, and storage. The primary goal of data acquisition is to effectively collect data from external sources and all the health system's components throughout the healthcare units. During the data transformation, transformation engines are capable of moving, cleaning, splitting, translating, merging, sorting, and validating data. Structured data such as that typically contained in an eclectic medical 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 validated against data quality rules. Finally, the 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. In summary, since there three functionalities can 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 aim to process all kinds of data and perform appropriate analyses for harvesting insights (Wald et al., 2014). In hospitals, this is particularly important for transforming electronic patient data into meaningful information that supports evidence-based decision making and meaningful use practices. This component has four major functionalities depending on the type of data and the purpose of the analysis: First, Hadoop/MapReduce is the most commonly used programming model in BA platform and provides the ability to process large volumes of data in batch form cost-effectively, as well as allowing the analysis of both unstructured and structured data in a massively parallel processing (MPP) environment (Watson, 2014).

Second, stream computing can support data processing in near real time or real time. Hospitals can track patient data in motion, respond to unexpected events as they happen and quickly determine next-best actions. With such a real-time analysis, no matter where the patient suffers a health emergency, even if they are away from home and in a different health administration domain, the configuration of his/her personal health monitoring device will be switched to an appropriate response format automatically, which will also contact a local healthcare provider for coordination. Third, in-database analytics refers to a data mining approach built on an analytic platform that allows data to be processed within the data warehouse. This functionality provides high-speed parallel processing, scalability, and optimization features geared toward BA, and offers a private and secure environment for confidential patent records.

Finally, social media analytics refers to informatics tools and frameworks to collect, monitor, analyze, summarize, and visualize social media data (Fan and Gordon, 2014). Prior research has indicated that this functionality 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). Put all together, 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 emphasize the ability to produce reports about daily healthcare services to aid managers' decisions and actions. This component has three functionalities: The first functionality yields general summary of data 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, to detect advanced warnings for disease surveillance, and to develop personalized patient care. Second, data visualization, a critical BA feature tends to extrapolate meaning from patient-generated data and displays them in visual ways (e.g., interactive dashboards and charts). These visualization reporting supports physicians and nurses' daily operations and help them to make faster, better evidence-based decisions. Third, real-time reporting, such as alerts and proactive notifications, real time data navigation, and operational key performance indicators (KPIs) is mainly gained from smartphones and personal medical devices. It can be sent to interested users or made available in the form of dashboards in real time for monitoring patients' health and preventing accidental medical events. Because these data interpretation functionalities can enhance the healthcare delivery in value-adding ways, the effective use of data interpretation component is proposed as a key facet of BA capability in health care.

Absorptive capacity

Absorptive capacity was conceptualized by Cohen and Levinthal (1990) to describe how a firm to absorb their knowledge. Absorptive capacity is defined as the ability to identify, assimilate, and exploit knowledge to help organizations acquire and sustain competitive advantage (Cohen and Levinthal, 1990; Zahra and George, 2002). 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. The role of absorptive capacity in organizational learning process attracts many researchers' attention. Earlier studies stress that firms' ability to obtain and apply knowledge becomes critical since knowledge per se cannot generate value (Malhotra et al., 2005; Cohen and Levinthal, 1990; Lichtenthaler, 2009). A substantial body of research applies the concept of absorptive capacity in various research stream, such as knowledge management (Alavi and Leidner, 2001), IT governance (Sambamurthy and Zmud, 1999), and IT business value (Bhatt and Grover, 2005). In IT business value research, researchers suggest that absorptive capacity plays an enabler of IT business value (e.g., Joshi et al., 2010; Malhotra et al., 2005). By analyzing secondary data from 110 firms, Joshi et al. (2010) conclude that absorptive capacity that is created through the use of IT applications can contribute to firm innovation.

In this study, absorptive capacity is viewed as a capability based on Robert et al.'s (2012) view. Taking this view, we examine how business value of IT, specifically for decision-making effectiveness results from a synergistic relationship between BA capability and absorptive capacity. Cohen and Levinthal (1990) originally identify three dimensions of absorptive capacity: identification, assimilation and exploitation. It is later extended into four dimensions: acquisition, assimilation, transformation, and exploitation of knowledge (Flatten et al., 2011; Zahra and George, 2002). This study follows this extended conceptualization and considers these four capacities together for 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. Transformation denotes the integration of new knowledge with current knowledge, preparing the knowledge ready for application (Zahra and George, 2002). Exploitation illustrates the process of using the "integrated" knowledge to improve organization's existing performance and generate new value. These four capacities reflect firms' ability to highlight and apply new knowledge, which is critical to firms' performance.

RESEARCH MODEL AND HYPOTHESIS DEVELOPMENT

Based on the discussion of the literature, we develop a research model to delineate the mechanisms by which BA 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 key mediating links: absorptive capacity. Figure 1 illustrates our research model.

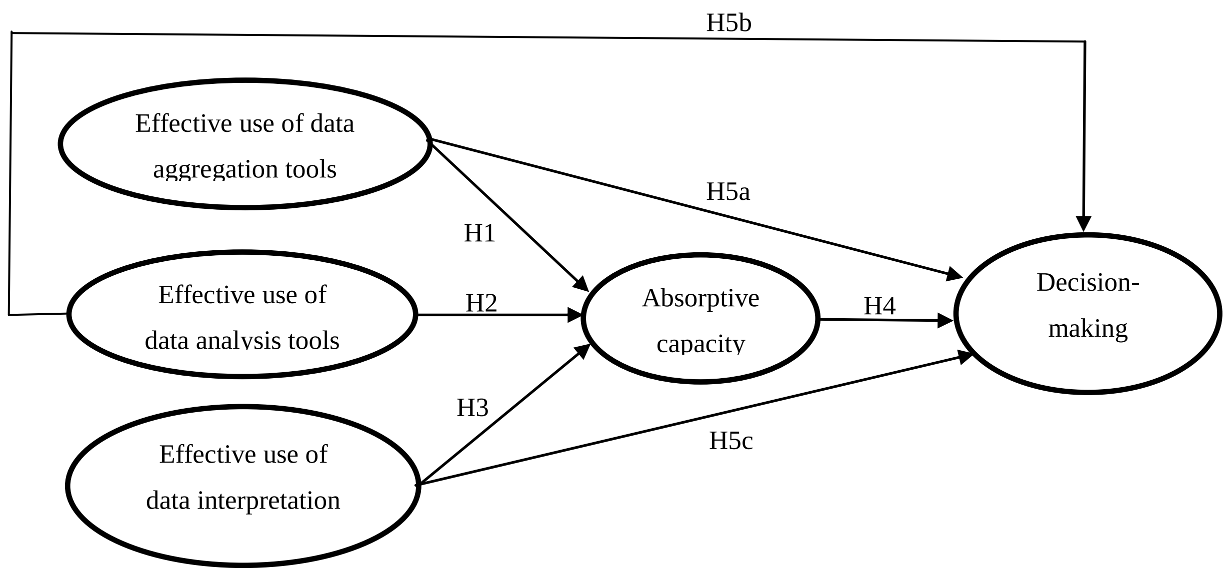

Figure 1. The proposed research model

BA capabilities and absorptive capacity

In health care, although acquiring and extracting knowledge from patient data appears to be a challenge due to privacy-preserving and trustworthy health infrastructure (Chen et al., 2012; Wickramasinghe and Schaffer, 2006), several studies have explored the main ways through which BA capabilities can help healthcare organizations achieve absorptive capacity (Wickramasinghe and 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 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 becomes an important tools to identify patterns of care and discover associations from massive healthcare records, thus providing a broader view for evidence-based clinical practice. In hospital settings, the use of clinical analysis tools in large longitudinal healthcare databases to identify knowledge about drug risk. By integrating BA algorithms into the legacy IT systems, medical staff can automatically acquire the 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 analysis, social media analytics allows healthcare organizations to discover knowledge from healthcare online communities (Fan and Gordon, 2014). Social media and its content generated by social interactions and communications among patients not only allows for exploring the incredible business values, but also can be regarded as a vital knowledge base for improving healthcare quality and patient satisfaction.

Third, the effective use of data interpretation tools can yields sharable information and knowledge such as 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. One case demonstrates the effective use of data interpretation tools well. U.S. healthcare alliance of approximately 3,000 U.S. hospitals, Premier, collects data from different departmental systems and sends it to a central data warehouse. After near-real-time data processing, the comprehensive and comparable clinical reports in terms of resource utilization and transaction level cost generated as a valuable knowledge are then used to help hospitals' managers recognize emerging healthcare issues such as patient safety and appropriate medication use.

In summary, 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 dependent upon its ability to leverage and implement BA tools, which is reflected in its BA capabilities. Hence, we hypothesize as follows:

> *Hypothesis 1 (H1): The effective use of data aggregation tools affects a healthcare organizations' absorptive capacity*.

> *Hypothesis 2 (H2): The effective use of data analysis tools affects a healthcare organizations' absorptive capacity*.

> *Hypothesis 3 (H3): The effective use of data interpretation tools affects a healthcare organizations' absorptive capacity*.

Absorptive capacity and decision-making effectiveness

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 practices. Firm with strong absorptive capacity can proactively make proper and fast decisions on business strategy and value chain activates than their competitors (Elbashir et al., 2011; Francalanci and Morabito, 2008). In the context of new product development, firms can make timely decisions toward product development and effectively commercialize innovate idea into new product if they can create new knowledge more efficiently than other competitors (Lin et al., 2015). With the same logic, in healthcare, a high level of organizational absorptive capacity enables organizations to transform clinical data into insights which lead to speed up decision-making process and quickly respond to customer needs. Hence, the following hypothesis is presented as:

> *Hypothesis 4 (H4): Absorptive capacity is positively associated with decision-making effectiveness in health care*.

The mediating role of absorptive capability

We propose indirect impacts of BA and analytical personnel in healthcare on decision-making effectiveness through the mediating role of absorptive capacity. Following the process view of organizations and Porter's (1985) value chain model, IT capabilities are viewed as VRIN resource to support secondary activities. This implies that IT capability is not directly involved in primary activities such as operations and marketing, but it can act as a supporting role in improving the performance of primary activities. With this view, Pavlou and El Sawy (2006) and

Robert et al. (2012) further highlight that absorptive capacity serves as a complement to IT capability in creating business value, which emphasizes that obtaining capabilities from the use of IT to increase organizational performance cannot be guaranteed unless organizations have enough capacity to identify, absorb, transform, and exploit the knowledge that is generated from IT.

Combining these arguments suggests 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 decision making processes, increase the quality of decision making, and deeper understand their patients. In contrast, without it, they are less likely to achieve superior decision-marking effectiveness. Hence, the following hypotheses are presented as:

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 for this study was the Taiwan's hospitals and listed in the most recently available list of hospitals published by the Joint Commission of Taiwan (JCT). The qualifying hospitals should have experience on BA investments for management and development of healthcare service. We posited that larger hospitals would be more likely to perform the BA activities. Thus, to be included in our study, a hospital has to be classified as medical center, regional hospitals or district hospitals and must have at least 100 beds. Local clinics and psychiatric hospitals were excluded, because they do not investment in BA because of their size. The 424 hospitals satisfied all the above criteria and were included in the survey.

This study focuses on whether organizations' decision making performance can be influenced by the use of BA systems. Thus, CEOs, CIOs, IT managers or senior IT staffs who actively involved in BA activities are the major subjects in this survey. We mailed one questionnaire to each hospital's primary contact. In total, 424 questionnaires were sent to potential participants. Of the 155 responses received, three of them were incomplete, resulting in a 35.84% response rate and 152 valid data points. Of these respondents, 26.97% (n=41) were from C-suite level executives, 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 participated hospitals have at least 200 employees. We recognized the difficulty and importance of finding respondents who can provide insights to various factors and so built in a selection filter by asking the participants to self-check against their experiences about BA before taking the survey. The responses revealed that 78.94 % (n=120) of the participants were working on BA projects at least five years. 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 Items

We developed multi-item measures by either adopting some scales previously validated in the existing literature and modifying them appropriately to fit the context or newly developing the scales while there is no validated scale currently in literature. Appendix 1 lists the measurement items used. Responses to all the multi-item measures were captured using seven-point Likert-type scales.

DATA ANALYSIS AND RESULTS

Given our research model and objectives, structural equation modeling (SEM) enjoys several advantages over other analysis techniques such as linear regression because SEM can examine proposed causal paths among constructs (Gefen et al., 2011). We analyzed the data using IBM Amos 20.

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 reliability for the measures

(Bollen and Lennox, 1991), with all values well above .70 (Nunnally and Bernstein 1994). As shown in Table 2, the CRs ranged from 0.93 and 0.98, well over the commonly accepted cutoff value of .70 (Hair Jr., 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
S.D.: Standard deviation; α: Cronbach's alpha, 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 2). 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 2 suggests the adequate divergent validity of the measures.

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 the four cross-functional collaboration factors were as follows: 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, .574 to .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 .80 (Hair, et al. 2009), and the standardized root mean square residual (SRMR) was .0557. The root mean square error of the approximation (RMSEA) is .046, which is less than .08. Thus, we concluded that our data adequately fit the measurement model.

Model testing

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 .95. SRMR and RMSEA were less than .08 for Model A. Then, a series of alternative structural models were tested against each other. After comparing the 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 result found 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. Then, 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 4 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 also compared to Model C and Model D. The results showed that Model E produced a significantly better fit to the data compared to Model C and Model D, and found that the effective use of data analysis and interpretation tools positively affect absorptive capacity. Thus, Hypothesis 2 and Hypothesis 3 were supported, but Hypothesis 1 was not supported. Finally, the proposed model (Model A) was compared to Model E, and 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 become insignificant after adding a medication (in this case, absorptive capacity). It mediated the relationships between the effective use of data analysis tools and the effective use of data interpretation tools on the one hand and decision-making effectiveness on the other, but 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 non-significant. As the direct effects of effective use of data analysis tools on decision-making effectiveness was not significant, hence 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, hence absorptive capacity 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 Cheung and Lau (2008) guided, we set 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], 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 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 decision-making effective ness was not significant, consistent with the aforementioned results. Thus, Hypothesis 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	$\Delta\ \chi2$	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.

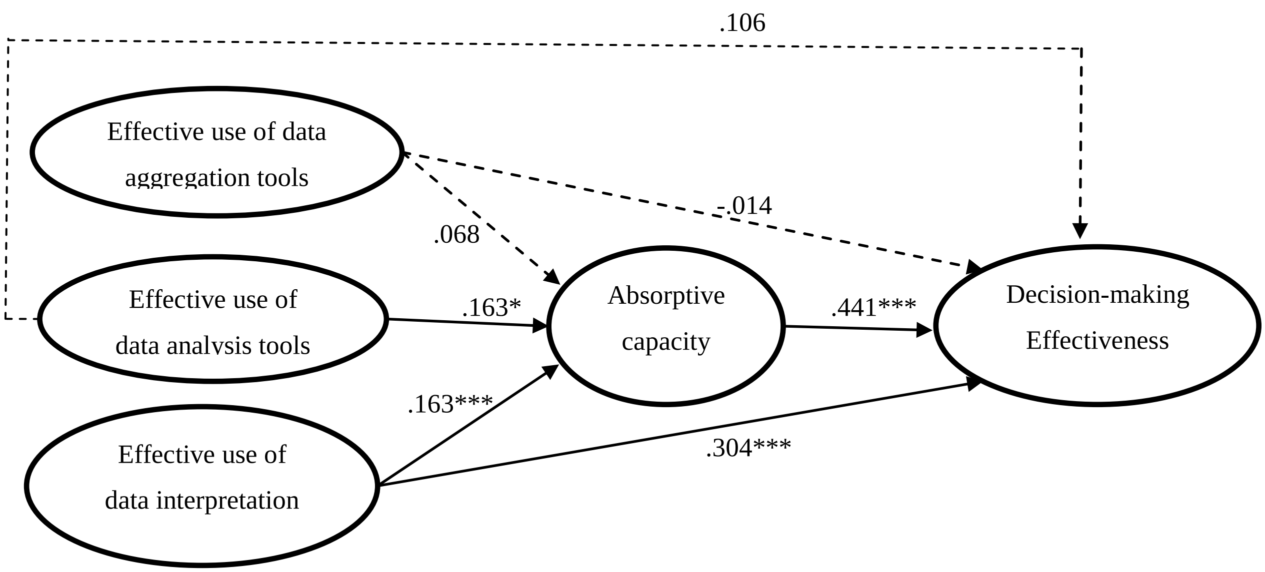

Figure 2. Path diagram and standardized estimates

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 central theme of this research is to advance an understanding of the way BA enables healthcare units to enjoy better decision-making effectiveness through the absorption of new knowledge from the use of BA systems. The empirical evidence collected for this study supports our three key findings. First, we conceptualize, operationalize, and measure the BA capability as a multi-dimensional construct formed by capturing the functionalities of BA systems in healthcare. Second, with respect to direst effect, we found that hospitals are likely to obtain valuable knowledge as they utilize the data interpretation tools effectively. Third, most importantly, 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. Based on these findings, we offer some insights regarding theoretical and managerial implications in the remainder of this section.

Theoretical contributions and implications

A compelling question in the IS literature, particularly in business value of IT research, is how the BA can be used to obtain business value since implementing BA systems is still in 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 deeper understanding of business analysis. To measure BA capability, few previous studies have modeled it as a one-dimension construct and merely focused on the examination of data analysis, but such an approach may unintentionally overlook other important facets of BA capability, such as the ability to visualize data. Business value of IT research has focused on a nominal view of the IT artifact, which it generally advocates the benefits of IT use, but no any specific technology mentioned in the article (Orlikowski and Iacono, 2001). Going beyond this view, the proposed construct draws on the view of IT functionality that allows to capture BA more fully by reviewing its functionalities and how it actually implement in healthcare units to conceptualize the BA capability. This conceptualization is the first step towards building a much needed body of knowledge on business value of BA and provides researchers 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 by adopting the absorptive capacity perspective that is rooted in organizational learning theory and knowledge-based view. Our results demonstrated how knowledge absorption matters in the use of BA for decision making process by examining its mediation role. This implies that BA per se does not create business value, but organizations' abilities to identify, extract, transform, and utilize knowledge can transfer the impact of BA use into organizational performance, leading to speed up the decision making, improve the quality of decision, more understanding on customers. Specifically, our finding suggests the effective use of data analysis and aggregation tools have no business value that affirms the view of IT productivity paradox in the healthcare context (Jones et al., 2012). However, the mediating role of absorptive capacity not only provides the mechanism how BA contributes to decision making practices, but only offers a new solution to IT productivity paradox puzzle in healthcare settings.

Implications for practice

For project leaders who is responsible for implementing BA systems, this study provides a set of interesting insights to scope their current projects: First, even if IT vendors have increasingly advocated the potential benefits of BA to be used in various business practices, BA implementation requires organizational changes. Except for technological issues, managers must also turn their attention on integrating knowledge governance into BA initiatives, which focuses on how to harness BA-generated knowledge. A strong knowledge governance protocol should add tremendous value during BA implementation. Second, our result shows that data interpretation is the most crucial capability that directly leads to decision-making effectiveness. Although BA can create summarized reporting or charts, the key to make 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 analytical training courses in areas to those employees who will play a critical support role in the new information-rich work environment that help organizations have a better opportunity to transfer data into to knowledge.

CONCLUSION

Notwithstanding the above-mentioned contributions and implications, our study is subject to some limitations. First, different industries have different needs or goals of using BA solutions. We targeted at healthcare for this study. The generalizability of the results is limited, because data were only collected from a limited sample consisting of Taiwan’s hospitals. Second, the sample size for validating the BA capability scale was relatively small, while the representativeness of our sample may overcome the sample size issue. More than 70% of participants in this study served as senior IT executives who could provide strategic views of BA in the healthcare organizations. Meanwhile, by carefully taking various steps for scale development, we tried to minimize the potential bias. Finally, given its exclusive focus on BA capability, our study does not consider other possible factors leading to BA success.

In response to the limitations of the current study, we offer some suggestions for future research. A more comprehensive study now need to focus on other factors that may be an enabler, moderating or mediating role for this path. As business value of IT research suggested, several human IT resource (e.g., 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) should be included to be examined. Also, rather than examining the aforementioned factors with singular causation and linear associations, future study can capture the complex interactions of the interdependencies among BA capabilities and other organizational elements, and examine how different configurations cause improved business value (Kung et al., 2015).

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

Appendix 1: 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 trend to improve healthcare services.
2. Predict pattern of care to response patient needs.
3. Analyze data in near-real or real time that allows responding to unexpected clinical events.
4. Analyze social media data to understand current trend from a large population.

Effective use of data interpretation tools (Newly developed)

1. Provide the 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 and 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; LaValle et al., 2011; Sanders and 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 on customers.

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