An Integrated Big Data Analytics-Enabled Transformation Model: Application to Health Care

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ABSTRACT

A big data analytics enabled transformation model based on practice-based view is developed which reveals the causal relationships among big data analytics capabilities, IT-enabled transformation practices, benefit dimensions and business value. This model was then tested in healthcare setting. Through analyzing big data implementation cases, we sought to understand how big data analytics capabilities transform organizational practices, thereby generating potential benefits. In addition to conceptually defining four big data analytics capabilities, the model offers a strategic view of big data analytics. Three significant path-to-value chains were identified for healthcare organizations by applying the model, which provides practical insights for managers.

KEYWORDS: Big data analytics, IT-enabled transformation, practice-based view, health care, content analysis

1. INTRODUCTION

The arrival of the "*Age of Big Data"* presents, to many industries and the firms that populate them, heretofore unprecedented opportunities and novel complexities. A number of benefits from adopting big data analytics into business practices have been recognized by researchers and technology consultants (or vendors). Big data analytics is acknowledged to have the potential to fill the growing need of healthcare managers to manage the surge of clinical data that supports evidence-based medical practice (Bates et al., 2014) and improves quality and efficiency of health care delivery (Ghosh & Scoot, 2011; Murdoch & Detsky, 2013). Proponents of the application of big data in the United States claim that when properly applied, data analytics in the healthcare industry helps cut costs by $300 million annually as well as improve the management of lifestyle-induced diseases, streamline administrative complexities, and improve interfaces between customers and providers (Manyika et al., 2011). However, in fact, exponentially increasing volumes of data in various formats from sources challenge a healthcare organization's traditional data management capabilities. Much of their rich electronic healthcare record data set is "perceived as a by-product of health care delivery, rather than a central asset source for competitive advantages" (Murdoch & Detsky, 2013, p.1351). To fully enjoy the benefits brought forth by big data analytics, a need exists to shift the focus from technology tools to examine and present the managerial, economic, and strategic impacts of big data analytics and explore the effective path of how big data analytics can be leveraged to deliver business value for healthcare organizations (Raghupathi & Raghupathi, 2014; Wang & Hajli, 2017).

Research on big data analytics has primarily focused the role of big data analytics capability and examined its direct effect on firm performance (e.g., Akter et al., 2016; Gupta & George, 2016; Işık, Jones, & Sidorova, 2013). However, eminent scholars criticize that IT resource and capability alone may not unequivocally facilitate firm performance (Bromiley & Rau 2014; Melville et al., 2004). In the same vein, studies of the IT productivity paradox have suggested that IT could not directly yield significant productivity gains in healthcare settings (Jones et al., 2012). Practice-based view (PBV) has been proposed to bridge this missing link and to help researchers and practitioners in understanding how the critical elements of practice interact with IT tools (Huang et al., 2014; Shollo & Galliers, 2016). In the specific context of health care, scholars have adopted this view to provide in-depth insights to healthcare practitioners on how IT tools can be used in improving clinical practices (Goh, Gao, & Agarwal, 2011; Jensen & Aanestad, 2007). Thus, we argue that by adopting PBV this will build a more complete picture of how big data analytics can be effectively leveraged to deliver business value. However, there has to date been little attention given to improving our understanding of the impact big data analytics on organizational activities and business processes (Shollo & Galliers, 2016). We seek to fill this gap by developing a conceptual model of big data analytics enabled transformation based on the PBV proposed by Bromiley & Rau (2014), and use this as a framework to examine how big data analytics capabilities facilitate IT-enabled transformation practices and thus contribute to business value for healthcare organizations.

Our contribution to the literature on big data analytics is twofold. First, drawing on the PBV, we develop a big data analytics enabled transformation model (BDET) that links big data analytics capabilities to IT-enabled transformation practices and then to benefits and business value. As PBV offers a new perspective to complement the extant strategic views, this model provides a deeper understanding of how healthcare practices can be facilitated through the implementation of big data analytics. Secondly, BDET model is applied to the healthcare context. The elements, pair-wise connections, and path-to-value chains of our BDET model are extracted from the real-world cases which show easy-to-follow scenarios and provide new insights and guidance for healthcare practitioners.

The remainder of this paper is structured as follows: the next section serves as our theoretical background, which leads to the development of the research model; followed by our research method, findings and discussions, contributions to research, implications for practice and recommendations, then limitations and future research directions are discussed as our conclusion.

2. THEORETICAL BACKGROUND AND RESEARCH MODEL

The theoretical development begins with an introduction of the Big Data Analytics-Enabled Transformation Model that used the practice-based view to explain how big data analytics and its generated capabilities enable organizations to develop inimitable practices, which in turn creates their business value. We then present big data analytics architecture components from which big data analytics capabilities are generated.

2.1 A model of big data analytics-enabled transformation

We draw on PBV as a theoretical underpinning to develop our research model. PBV emerging from strategic management 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 needed for performance in a given context (Bromiley & Rau, 2014). The model of big data analytics-enabled transformation model constructed for this study is presented as Fig 1.

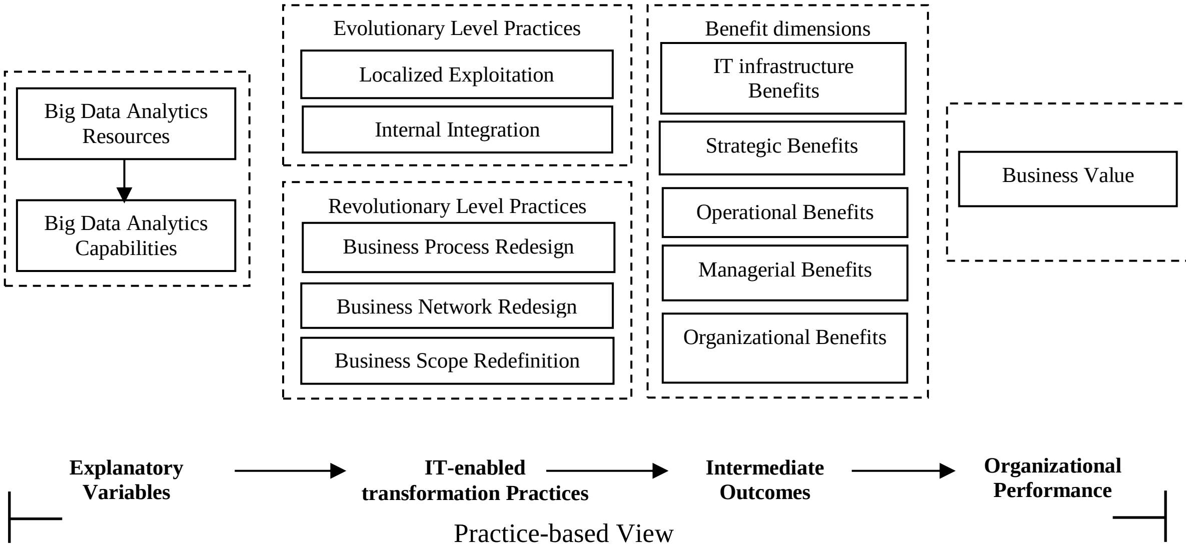

Figure 1. Big Data Analytics-Enabled Transformation Model

As shown in Figure 1, the linear progress path of our research model follows a PBV framework developed by Bromiley & Rau (2014): 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). Bromiley and Rau's (2014) PBV framework demonstrates how different performances are manifested in firms' execution of various practices that are facilitated by explanatory factors. In this framework, the 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 the PBV. 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, 2005). The use of practice itself is important for both intermediate and organization performance outcomes (Igira, 2008; Tallman & Chacar, 2011). The explanatory variables can be viewed as antecedents or enablers of the practice. The explanatory variables are not specified in the Bromiley and Rau's (2014) PBV model which allows for idiosyncratic interpretation and applications.

2.1.1 Explanatory variables: Big data analytics capabilities

Drawing on the PBV, the first step to construct the big data analytics-enabled transformation model is to define the explanatory variable, which in this study is big data analytics capabilities generated from big data analytics resources. Big data analytics resources – that is, big data analytics architectural components can create big data analytics-specific capabilities. In previous studies, 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. Recently, Gupta & George (2016) emphasize that firms have to develop big data analytics-specific capabilities to attain organizational performance. Gupta & George's study has identified various resources such as data, managerial and technical skills, and data-driven culture that in combination build a big data analytics capability, and this capability create the operational and strategic business value (e.g., reduced inventory and cost savings).

Big data analytics comprises an integrated array of aggregation techniques, analytics techniques, and interpretation techniques that allow users to transform data into evidence-based decisions and informed actions (Cao et al., 2015; Jagadish et al., 2014). We identified three architectural components of big data analytics from its tools and functionalities: data aggregation, data analysis, and data interpretation, by reviewing the relevant academic literature (e.g., Raghupathi and Raghupathi, 2014; Ward et al., 2014) and technology tutorials (e.g., Hu et al., 2014; Watson, 2014).

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 aggregated by three key functionalities from data aggregation tools: acquisition, transformation, and storage (Raghupathi & Raghupathi, 2014).

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.

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 include: 1) general clinical summaries reporting such as historical reporting, statistical analyses, and time series comparisons, 2) data visualization, a critical big data analytics feature is to extrapolate meaning from external data and perform visualization of the information, and 3) 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 (Wang & Byrd, 2017).

2.1.2 IT-enabled transformation practices

Next on the model, IT-enabled transformation practices serve a pivotal role in transforming the big data analytics capabilities into the intermediate outcomes. IT-enabled transformation practices are 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 (Lucas et al., 2013; Venkatraman, 1994). Venkatraman's (1994) IT-enabled transformation model is used to classify the different level of transformational practices which include localized exploitation, internal integration, business process redesign, business network redesign, and business scope redefinition. 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.

2.1.3 Outcomes

A multidimensional IS benefit framework developed by Shang and Seddon (2002) is employed to conceptualize the intermediate outcomes of our model. Shang and Seddon's framework (2002) was built on a large body 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. Justification of applying Shang and Seddon's benefit dimensions as the outcome of our model is threefold. First, 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. Finally, Shang and Seddon (2002) provide a clear guideline for assessing and classifying benefits from IT architecture.

Table 1. IS benefit framework (adopted from Shang & Seddon, 2002)

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 strategies.	• Changing work patterns • Facilitating organizational learning • Empowerment • Building common vision

2.2 Big data analytics-enabled transformation

A large body of research has converged on the notion that use of big data analytics is a powerful tool to enable business transformation within organizations. A review of the existing big data literature reveals three consistent findings about big data analytics-enabled transformation: (a) big data analytics and its generated capabilities are fundamental in organizational transformation and performance; (b) Big data analytics-enabled transformation occurs when organizations improve their organizational practices enabled by big data analytics technologies; (c) The potential benefits of big data analytics-enabled transformation should be conceptualized by a multidimensional and comprehensive benefit framework.

First, IT resources consist of IT infrastructure, human IT resources, and IT-enabled intangibles that the firm can use to improve business processes (Bharadwaj, 2000), whereas IT capabilities can be triggered by the integration of IS/IT resources, which ultimately impact competitive advantage (Wade & Hulland, 2004). IT capability literature further asserts that IT resources determine a firm's IT capabilities and the positive impact of IT resources on IT capabilities has been empirically validated (Wang et al., 2012). Several big data studies argue that a firm's unique big data analytics capability can be constructed by the configurations of available big data analytics technological resources (LaValle et al., 2011; Wixom et al., 2013) or the synergetic combination of valuable, rare, imperfectly imitable and non-substitutable organizational resources (Işık et al., 2013), and this capability results in superior organizational performance (Gupta & George, 2016; Trkman et al., 2010).

Second, effective transformations within organizations can be achieved through IT-enabled transformation practices (Huang et al., 2014; Markus, 2004). The idea of identifying practices that are facilitated by IT has come to the fore in Venkatraman's (1994) IT-enabled transformation model. Venkatraman's model is one of the first to identify a set of organizational change practices executed through IT/IS supports. Venkatraman's (1994) model consists of two levels, evolutionary and revolutionary, which are formed by two (i.e., localized exploitation and internal integration) and three (i.e., business process redesign, business network redesign, and business scope redefinition) practices respectively. Later on, Markus (2004) proposed techno-change management practices (e.g., changes in business process and workflow, new job designs, new skills training, restructuring business units, changing HR policies, reallocated resources and new incentives) to ensure adequate resources to assist in accomplishing organizational change with IT. These studies emphasize the outcomes in successful transforming organizations are realized through their IT-enabled transformation practices, rather than from their investment in IT alone.

Inspired by the above studies, the idea of identifying practices that are facilitated by big data analytics systems has come to the fore in big data research. A case study in an airline company provided by Watson et al (2006) find that a set of practices induced by real-time data warehousing and business intelligence, such as developing co-existence of strategic and tactical decision support and changing downstream decision-making and business processes can dramatically improve their profitability. Recently, Shollo & Galliers (2016) have identified that the problem articulation and data selection practices (e.g., articulating new distinctions and different perspectives) triggered by big data analytics systems enable organizations to transform new insights into organizational knowledge that can be used in making decisions and taking actions. In this line of thought, we believe that to transform organizations by big data analytics, organizations must implement appropriate transformational practices in order to create superior business value.

Third, the outcomes of IT-enabled transformation are not just a matter of increased productivity or efficiency. They are more related with new ways of doing business and achieving organizational level performance that may include not only tangible business value such as cost savings, but also intangible values such as increased flexibility and quality improvement (Melville et al. 2004). The difficulty in assessing the outcomes of IT-enabled transformation arises from the two facts that value from implementing new IT needs a period of time to be fully realized (Melville et al. 2004). Previous studies have provided the simple frameworks to evaluate IT business value (Melville et al. 2004). However, big data analytics can result in various benefits for users. For example, 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. Therefore, a comprehensive framework for recognizing the potential benefits of using big data analytics should be developed.

3. RESEARCH METHOD

3.1 Research Design and Approach

The epistemological foundation of this study is grounded upon the interpretivist paradigm. The multiple case study method is particularly applicable for interpretivist research in IS where "an understanding of the context of the information system, and the process whereby the information system influences and is influenced by the context" is preferred (Walsham, 1993, p. 4-5). Another reason for the recognition of multiple case studies as a research approach is the nature of the research question that is being investigated. Practice based research assumes that practices are observed, perhaps transformed and mostly studied with qualitative research methods (Huang et al., 2014; Peppard et al., 2014). In the same vein, Kohli & Grover (2008) suggest that a better way to increase a broader understanding of companies' new IT investments payoff is to learn from their success stories and observe their practices. These stories are useful sources for the preliminary stage of a research issue (Yin, 2008) and for creating theoretical constructs and propositions (Eisenhardt & Graebner, 2007). As this study aims at producing an understanding of how big data analytics influences the bundling of IT-enabled transformation practices and generates potential benefits from the enterprise perspective, it is appropriate to choose the multiple case study approach.

Our approach is to analyze big data analytics implementation projects based on case materials that delineate the effects big data analytics had on business value in healthcare organizations. We specifically studied the statements used to illustrate how big data analytics capabilities, triggered by its functionalities lead to improvements in IT-enabled transformation practices, thereby increasing potential benefits for health care organizations. By gradually decomposing these statements from case materials, the elements that altogether shape a cause-and-effect structure can be explored (Mueller et al., 2010). 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 et al., 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. By coding the statements evident in the case material, we analyzed and structured these statements using our proposed model that builds on the logic depicted in Figure 1. 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 complete path-to-value chain linking big data analytics and business value. These patterns identified across multiple cases may help us to gain an understanding of big data analytics' business value in health care.

3.2 Data Collection

Several studies have relied on case materials to explore the value of emerging technologies (e.g., Mueller et al., 2010). However, one common limitation of these studies is that the materials chosen for creating their model are provided from IT vendors and companies and thus may be potentially biased. Usually companies only report their "success" stories and vendors showcase 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 only from academic databases which may provide more rigorous and objective statements.

Our cases were drawn from case material of 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 were 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 (Appendix A) that adopted big data analytics.

Of these cases, 86% are from North America (22 cases from the United States; 2 from Canada), 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 “leaders” 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 and revenue.

3.3 Research Process and Data Analysis

We generally followed the three-step coding process: preparation, organizing and reporting provided by Elo & Kyngäs’ (2008) to extract insights from the cases to build our BDET model.

3.3.1 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 and healthcare informatics and followed a concept-centric approach suggested by Webster and Watson (2002) to develop our initial list of element coding. 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.

3.3.2 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 the definitions of the layers and elements of the BDET model (See Table 1 and Appendix B) 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 the meaningful use of EHR practice, we introduced a summary overview of meaningful use objectives and measures provided by Blumenthal & 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). 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 expert panel consultant initiated the selecting of statements (the analysis unit) from all 33 case descriptions that illustrate the path-to-value chain. A statement was selected if it describes how big data analytics contributes 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 and attached the initial labels relating to the layers (i.e., big data analytics resources, big data analytics capabilities, practices, and benefits) and elements (i.e., data aggregation, analytical capability). As the core layers and elements emerged, the coders initiated axial coding to explore the various sub-elements and identify the connections between them in order to develop more precise explanations of what big data analytics resources, capabilities, practices, and benefits are, what cause them, and the benefits that arise because of them. These sub-elements were abstracted from the statements to describe the content of the elements (Marshall & Rossman, 1995) and move beyond description to a higher level of abstraction (Urquhart et al., 2010). As second example shown in Appendix C, an passage captured from Spruit et al. (2014) states that big data analytics allows Dutch long-term care institution to group all medical incidents by using a SQL query and report the number and root cause of incidents at a certain time of day. This passage was labeled as “big data analytics capability” and “analytical capability” during the open coding, and subsequently the sub-element “explore the causes of occurred medical events from relational databases” was created to describe the analytical capability during the axial coding. In the final step of coding, selective coding focused on finalizing the codes (or developing new elements in some cases) by comparing and contrasting other similarly coded elements as well as the relationships and patterns that emerged during axial coding. As a result of coding process, the path-to-value chains emerged and became evident. Appendix C presents two examples of statements and the open, axial and selective codes that were applied to them.

Agreement between two coders in expert panel established the elements, sub-elements, connections, and 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. The sub-elements were revised, refined, merged to reach a more abstract level of conceptualization. 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.

Finally, a content analytic technique, frequency analysis 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.

4. RESULTS AND DISCUSSIONS

Building on the theoretical foundations and conceptualization summarized in Figure 1, this section presents our BDET model gained from the analysis of 33 case descriptions and 105 path-to-value chains. In the following section, we discuss our results according to three distinct perspectives. In Section 4.1, we break down each element presented in the BDET model by showing the total number of occurrences (i.e., big data analytics architectural layers, big data analytics capabilities, IT-enabled transformation practices and benefits). In Section 4.2, we discuss the pair-wise connections between the elements in the BDET model. In Section 4.3, we discuss the path-to-value chains connecting all the elements describing big data analytics' business value.

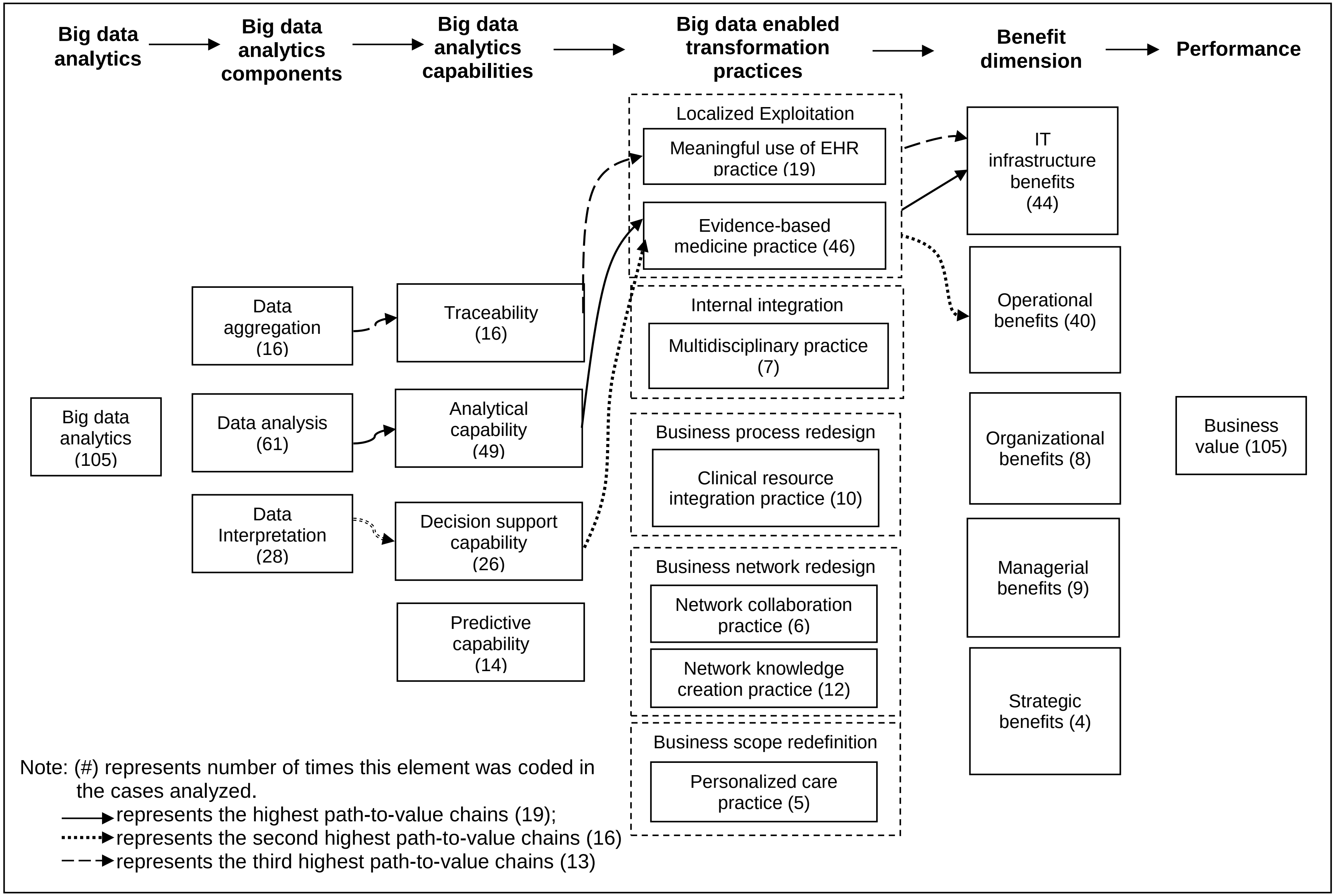

Figure 2. The Results of the Big Data Analytics-Enabled Transformation Model

4.1 Elements

4.1.1 The elements of big data analytics architectural component

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 resource in health care

<table>
<tr><th>The elements of big data analytics resource</th><th>Sub-elements</th><th colspan="2">The number of occurrence</th></tr>
<tr><td rowspan="3">Data aggregation</td><td>Data warehouse (SQL database, NoSQL database, and cloud-based database)</td><td>6</td><td rowspan="3">16</td></tr>
<tr><td>Hadoop distributed file system</td><td>6</td></tr>
<tr><td>Extract-transform-load (ETL)</td><td>4</td></tr>
<tr><td rowspan="5">Data analysis</td><td>Descriptive analysis</td><td>18</td><td rowspan="5">61</td></tr>
<tr><td>Online analytic processing (OLAP)</td><td>15</td></tr>
<tr><td>Data mining</td><td>13</td></tr>
<tr><td>Text mining/Natural language processing (NLP)</td><td>9</td></tr>
<tr><td>Predictive modeling</td><td>6</td></tr>
<tr><td rowspan="2">Data interpretation</td><td>Visual dashboards/systems</td><td>18</td><td rowspan="2">28</td></tr>
<tr><td>Reporting systems/interfaces</td><td>10</td></tr>
<tr><td colspan="2">Total</td><td colspan="2">105</td></tr>
</table>

4.1.2 The elements of 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 in Health Care

The elements of big data analytics capabilities	Sub-elements	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	

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; 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). Amarasingham et al. (2014) indicate that the difficulty to customize legacy healthcare information systems for predictive models would limit 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 of predictions.

4.1.3 The elements of IT 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 IT Enabled Transformation Practices in Health Care

The elements of IT enabled Transformation Practices	Sub-elements	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 medical events (or patient treatments) 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	

4.1.4 The elements of benefit dimension

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, 2014a), 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

The elements of potential benefits	Sub-elements	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 traditional database environments	3	
	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	

4.2 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).

4.2.1 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 resources			
	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

4.2.2 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., Raghupathi & Raghupathi, 2014; Ward et al., 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 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

4.2.3 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

4.3 Discussion of path-to-value chains

Three path-to-value chains were observed most frequently as shown in Fig. 2. 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.

4.3.1 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, an open collaborative research and innovation center, has emphasized that analyzing findings from previous clinical studies could be used to translate new evidences into routine clinical processes and thus drive successful evidence-based medicine (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 & 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 efficiency of evidence-based medicine practices, which in turn facilitates IT infrastructure benefits.

4.3.2 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.

4.3.3 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.

5. THEORETICAL AND MANAGERIAL IMPLICATIONS

5.1 Theoretical implications

This study has several theoretical implications for big data analytics research. First, instead of simply focusing on the impact of big data analytics on business value, we have developed the big data enabled transformation model based on practice-based view to further understand how big data analytics impacts the transformation practices in healthcare organizations. We believe this is among the first attempts to systematically capture the causal relationships among big data analytics capabilities, IT-enabled transformation practices, benefit dimensions and business value. Second, our study reveals the essential elements, connections, and path-to-value chains for an understanding of organization transformation through big data analytics. To the best of our knowledge, this is a first study that took such unique approach integrating a prominent IS theories, applying the new perspectives to a current IT innovation to show the “causal chains” of IS business value. With this approach, we have provided empirical evidence that big data analytics has a significant impact on improving meaningful use of EHR and evidence-based medicine practices.

Finally, PBV promotes a research approach that “examines publicly known, imitable activities, or practices amenable to transfer across firms." (Bromiley & Rau 2014, p.1249). Healthcare is a fertile domain for this type of research because there are many “publicly known” and “imitable activities.” Therefore, we chose the healthcare industry to further test and validate the applicability of our model. As practice-based view offers a new and different perspective to complement the extant strategic views such as resource-based theory (Bromiley & Rau 2014), we set out to explore the potential explanations for performance variation from common practices.

5.2 Practical implications

Our findings offer practical insights and guidance for healthcare practitioners who are engaged in implementing big data analytics. First of all, decision support is one of the crucial big data analytics capabilities due to its ability to create meaningful clinical reports. 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. Thus, it is important that healthcare organizations provide analytical training 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 need.

Second, 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. 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. To comply with the Patient Protection and Affordable Care Act (PPACA) of 2010, healthcare organizations need to keep detailed and updated data. Our results show that this capability is still underutilized maybe because healthcare managers have not recognize the potential benefits or are cost sensitive. Our result demonstrates the elements involved in this path-to-value which managers could try to develop and to include to their repertoire.

Finally, although the frequency counts of the path-to-value chain the predictive 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. For example, one of our cases shows that predictive analytics supports Beth Israel Deaconess Medical Center's home health care by predicting patient illness, to quickly deploy nurses to where the patient suffers a health emergency. This reduced expensive emergency department visits. It also increased collaborating with local healthcare providers for care coordination (Halamka, 2014).

6. CONCLUSION

Notwithstanding the above-mentioned contributions and implications, our study is subject to the 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 analytics technologies to enjoy the benefits we presented by our findings.

Our 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 the BDET model and our findings with quantitative analysis method 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 analytics 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. 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.

In conclusion, not only has this study focused on identifying the big data analytics capabilities, but also we have developed a Big Data Analytics-Enabled Transformation Model based on Bromiley & Rau's (2014) practice-based view. While PBV purposely define practice in an ambiguous manner to accommodate the idiosyncratic nature of such construct, our study extends PBV by considering the IT-enabled transformation practice in health care as a practice variable and big data analytics capabilities as an explanatory variable. As a result, this study may provide a good starting point in opening the “black box” of how big data analytics capabilities impact transformation practices in healthcare.

Appendix A. 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 (2015)

Appendix B. 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); Wang et al. (2016)
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); 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	Delen (2014); Negash (2004)
Evidence-based medicine	Integrate individual clinical expertise with the best available external clinical evidence from systematic research	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 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.	Schleidgen et al. (2013)

Appendix C. Coding Examples

Statement A	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>Big data analytics resources</u>, <u>Data aggregation</u> *Data storage by dimensional models* <u>Big data analytics capabilities</u>, <u>Traceability</u> *Track medical events based on the rules that built on hospital claims* <u>Practices</u>, <u>Meaningful use of EHR</u> *Generate lists of patients by specific conditions to use for quality improvement* <u>Benefits</u>, <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 chains: Data aggregation →Traceability→ Meaningful use of EHR practice →IT infrastructure benefit

Statement B	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,	<u>Big data analytics resources</u>, <u>Data aggregation</u> *Collect data from multiple sources and integrate into a system*	• Comparing this statement to other similarly coded elements (i.e., data aggregation component,

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)	Big data analytics capabilities, Analytical capability *Explore the causes of occurred medical events from relational databases* Practices, Evidence-based medicine *Explore the fact from medical events to improve a specific outcome* Benefits, Operational benefit *Understand on incident locations and causes to improve workflow efficiency*	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

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