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BIG DATA RESOURCE MANAGEMENT IN BUSINESS: A MULTIPLE-CASE ANALYSIS

SHOUHONG WANG
UNIVERSITY OF MASSACHUSETTS DARTMOUTH
swang@umassd.edu

HAI WANG
SAINT MARY'S UNIVERSITY
hwang@smu.ca

ABSTRACT

Big data resource management has become an essential component of comprehensive business models for business organizations. Yet, few business models based on real-world business cases of big data management have been reported in the literature. This study collects and examines sixteen (16) business cases of data resource management in the big data wave. The qualitative data analysis of the multiple cases reveals a business model of big data resource management. The business model of big data resource management indicates that strategic use of data, design of requirements, information technology implementation, and outcome are the major constructs of big data resource management. These four constructs form feedback loops with causal relationships between them.

Keywords: Big data; big data resource management; business model; conceptual model; case analysis; qualitative data analysis.

INTRODUCTION

The world has been exploring big data for years [3,8,18,66,81]. Big data are characterized by volume, velocity, variety, and veracity [76]. The reality of big data raises challenges and opportunities for the entire society. The white paper [56] created by a group of prominent researchers in the big data filed summarizes the phases of big data processing: acquisition and recording, extraction and cleaning, data integration and representation, data modeling and analysis, and interpretation. The white paper suggests that the major challenges associated with big data include heterogeneity, scale, timeless, privacy, and human collaboration [56]. The characteristics of big data would make the traditional techniques of data collection, storage, analysis, and utilization inadequate or irrelevant.

Nowadays business organizations are seeking information technology (IT) solutions to big data. The major stream of research of big data in the business field has been business intelligence or business analytics [11,12,54]. While there have been advances in business intelligence and analytics during the past years after the big data declaration, traditional relational databases and conventional analytical tools are still the major technologies for business enterprises in dealing with business big data. Few novel big data theories or analytics tools beyond techniques of cloud data storage have applied to business organizations. Big data is merely a contemporary term of IT-enabled data resource management [16]. While the true meaning of big data for business can still be debatable, a practical approach to big data is to manage and utilize various available data to add value to the business [1].

To explore the real meaning of big data in business and to search a general business model of big data resource management in business organizations, this study collects real-world business cases of big data management, uses a quantitative data analysis of the multiple cases, and conceptualizes successful practices of business big data resource management. The rest of the paper is organized as follows. The next section is a review of literature of related work. The subsequent two sections describe the methods used for the qualitative data collection and coding to derive a conceptual business model of big data resource management, and explain the constructs of the conceptual business model. The final section discusses the limitations of the study and summarizes the study.

LITERATURE REVIEW

The term big data was used in the late 1990s [47,72]. The concept of big data has been evolving during the past two decades [79]. In a research report that addresses issues about how enterprises can manage data as a competitive catalyst, Laney [43] described three essential characteristics of big data: volume, velocity and variety. During the subsequent decade, numerous V's have been discussed in the big data community to characterize big data: visualization [24], veracity [60], variability [23], and value [27].

Big data challenges could mean differently depending upon the types of fields [42]. Big data is not limited to the business sector, and many other sectors, such as medical, bio-informatics, government, military, global economy, legal system, environment, astronomy, global social system, homeland security, cybersecurity, meteorology, etc., are all facing the big data problem. The Federal Big Data Commission [69] presented ten typical big data projects, and, surprisingly, none of these good big data projects came from the private business sector. In fact, the magnitudes of volume, velocity, variety, or veracity of data in business organizations are not as big as that in many other sectors. In other words, informative data for a particular business organization are usually not really big. First, a business organization uses big data for decision making. The scope of decision making in a business organization can never go beyond the boundary of the organization. Compared with, for example, global economy [21,38,83], business organizations' big data are rather small. Second, business data is time sensitive. The old business data are unlikely to be of much relevance to dynamic business decision-making or business planning. Compared with, for example, sciences [33,36,80], aged big data are unlikely to be useful for a business organization. Third, the big data used for business are typically structured transactions, although unstructured textual data, such as social media marketing and customer services, could be involved. Compared with, for example, homeland security [10,34,35], business organizations are typically dealing with much less heterogeneous data. Thus, the most important "V" of big data for business is value.

Business organizations are using big data to improve or innovate their business models by finding new ways to generate profits [75]. On the other hand, big data may trigger confirmation bias or illusions of control, and business organizations should establish build-measure-learn-loop cycles for fast verification of managerial hypotheses [61]. To explore the true meaning of big data for business, research [32,61,75] has been investigating the relationships between big data and business models. Business model is a broad term used in the business community to describe the strategy, the design of the organizational structure, the utilization of resource, and the value creation chain of a business organization [28,82]. The value creation chain of a business model describes value discovery, value creation, and value realization in the organization [53]. A business model can describe the organization from three perspectives: economic, operational, and strategic [50]. The economic perspective focuses on revenue and profit generation. The operational perspective presents internal business processes and infrastructural design for value creation. The strategic perspective projects how the organization develops competitive advantages for sustainable growth. A complete business model of the organization represents a comprehensive framework and can be composed of elementary business models at economic, operational, and strategic levels [51,63]. For example, a revenue model [2] identifies which revenue source to pursue, what product/service to offer, how to price the product/service, and who pays for the product/service. The resource-based view model [5,29,58], on the other hand, concentrates on the value of tangible and intangible resources in the organization's unique resource pool to present a unique identity and strategic competitive strength. Big data resources management should have its own elementary business model in the strategic and operational perspectives that can be integrated into comprehensive business models [9,71].

In summary, the literature has indicated that value is the holistic characteristic of big data for business. A complete business model for a business organization should include big data resource management to capitalize the big data resource for competition. This study is to develop a conceptual business model of successful business big data resource management at the strategic and operational levels based on an analysis of multiple real-world business cases.

ANALYSIS OF MULTIPLE CASES

Methodology

The overall objective of this study was to conceptualize a business model for business big data resource management through an analysis of multiple business cases. The qualitative data analysis methodology [78] was applied to this study. The study collected cases of business data resource management and then inducted a business model against these cases. The major attributes of qualitative data analysis, namely, data collection, coding, and analysis [19,22] applied to this study are discussed below.

Qualitative Data Collection

The major tactic used for data collection of this study was data triangulation [40] which combines multiple data sources to make the findings of this study convincing and accurate. The literature review used the Google search engine on the Internet and the ABI/Inform database to find case studies of business data resource management. The keywords used for the search included "business case", "story of big data for business", "business intelligence", "business analytics", "information technology for business", "business success case", "big data for business", and "data in business." The Google search engine is powerful to reach the wanted websites. The ABI/Inform database covers the major academic journals as well as industry periodicals in the areas of business, big data, information systems, information technology, and data resource management. Thus, the data collection was considered sufficiently comprehensive. Well documented cases of business data resource management in the literature were not as abundant as we thought. Some cases were too brief to analyze and were excluded. Sixteen (16) cases with sufficient contents of business data resource management in the big data era were used for this analysis. Appendix A exhibits a summary of these cases.

Qualitative Data Analysis

Qualitative data analysis retains contextual factors. A qualitative data analysis is conducted on the basis not only of a commonly used research methodology, but also of the contexts and situations in which the study takes place [14]. Qualitative data analysis is more than the coding and sorting of qualitative data, and involves holistic understanding the context of data [20]. The induction of this study in the present context of qualitative data analysis is to derive a conceptual model of effective business big data resource management by using the available business cases. This induction process applied the data triangulation tactic [40] which combines multiple sources of qualitative data to generate a generalized conclusion. The business big data management cases were collected by three MBA students as research assistants of this study. Each case was coded by two research assistants manually. They read each case sentence by sentence, and marked the statement with keywords or phrases. Each of the marked case with coding was reviewed by the third research assistant and the two project researchers. The two researchers of this project and the three research assistants conducted a so-called Joint Analytical Process (JAP), a team work setting for the qualitative data analysis. The reliability of qualitative analysis [78] is the key to meaningful qualitative data analysis. JAP reduces risks of misinterpretation of qualitative data. In this study, JAP places the emphasis on the key constructs of business data resource management in the successful business cases of data resource management. There were several JAP sessions for the entire qualitative analysis study, and each of the JAP sessions had a specific task. A JAP session is a series of knowledge sharing meetings of the participants to discuss a case or an issue [19]. Each JAP session has iterative cycles of meetings. JAP is different from brainstorming in that a JAP session must result in a consent conclusion among the participants. Figure 1 illustrates the qualitative data analysis process.

Before the first JAP session, the participants read the entire set of qualitative data to be analyzed. The first JAP session was to set a general guide for the analysis of multiple sources of qualitative data. A form of qualitative data analysis protocol [78] included the objective of analysis, specific questions for the analysis, and dictionary, as shown in Table 1.

Coding has been applied as a tool to facilitate qualitative data analysis to discover the patterns of data and the causal relations between sets of data [41,48,64,68]. The coding process was done manually in this study because no suitable software package was found.

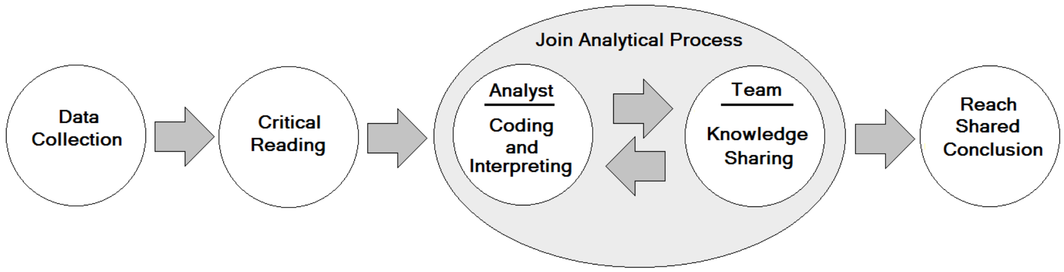

Figure 1: Process of Qualitative Data Analysis

Table 1: Outline of the Protocol Used in the Qualitative Data Analysis

Protocol Sections	Protocol Components
1. Overview of the set of qualitative data	*Objective:* To derive a conceptual model of effective business big data resource management *Key issue*: Constructs of business big data resource management and their relations.
2. Questions	1. What are the constructs of business big data resource management? 2. What are the causal relations between these constructs of business big data resource management?
3. Dictionary	Terminology Synonyms

The analysis had two types of components for the questions of the qualitative data analysis protocol: big data management constructs and their causal relations. Coding of big data management constructs was done using the In Vivo coding method [59], a grounded theory approach. For each of the sample business case, a sentence with a word or phrase related to a big data management construct was labeled with a "code" of data management constructs. Coding of causal relations is more semantic-based [65,73]. A causal relation between two constructs represents the unidirectional influence relationship between them, and could be expressed explicitly in the text using strong causation words (e.g., "lead to", "generate", "because", "since", "as", "after") to indicate a condition, a consequence, or a reason. Nevertheless, a causal relation between two constructs is often expressed implicitly though semantic information which could be related to ambiguous verbs in the text. The meaning of those ambiguous verbs (e.g., "spark", "encourage", "stimulate") are depending on the context of the text and the writing style.

The coding process includes two phases. In the first phase of coding, important constructs of big data management were identified and coded. This code dictionary was analyzed and formalized into constructs of big data management. In the second phase of coding, the causal relationships between the constructs were identified and coded. The two-phase coding process is illustrated in Figure 2.

To ensure the reliability of coding, the analysts exchanged general understanding of the research context and the overall qualitative data. The Cohen's Kappa Values were used to evaluate the inter-coder reliability of all the initial codes made by the individual analysts ($\kappa \geq 0.82$). The iterative data analysis process revised the codes to resolve inconsistent coding.

After the two-phase analysis, a conceptual business model of big data resource management was generated. The constructs of the model will be discussed with details in the next section. The descriptions of relations between the reviewed cases and the constructs of the proposed business model were summarized by using a meta-matrix [48]. The meta-matrix focused on the extent of support of the identified the crucial big data management constructs and their causal relations. The meta-matrix provides information for us to understand the extent of conceptualization a business model for business big data management. The meta-matrix includes the key points and explanation of the relevance of the coded big data management constructs and causal relations in each case. A brief version of the meta-matrix without detailed verbal descriptions is exhibited in Appendix B.

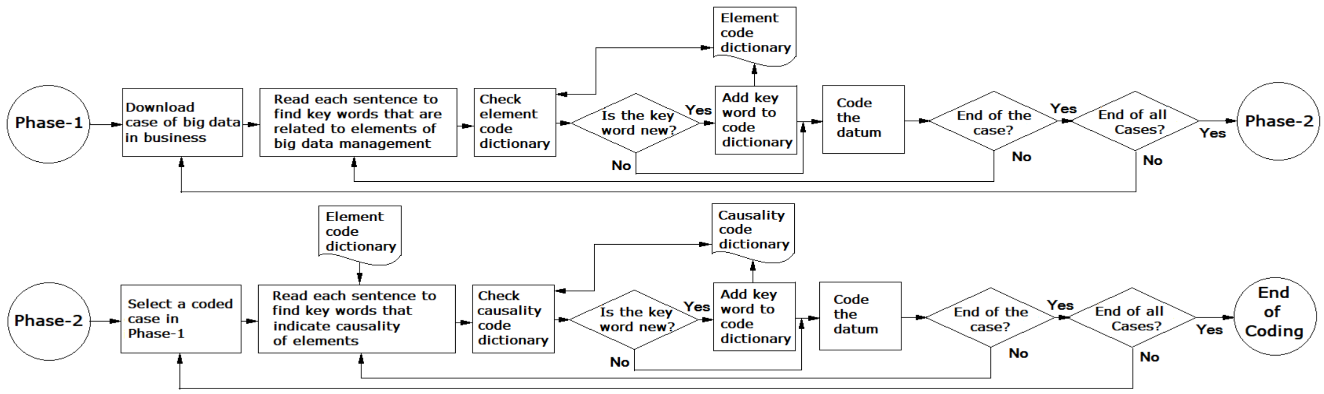

Figure 2: The Coding Process

THE CONCEPTUAL BUSINESS MODEL OF BIG DATA RESOURCE MANAGEMENT

This section explains the constructs of the derived business model in the context of big data resource management.

Strategic Use of Data

Harvesting big data is an organizational venture for business. A business organization must define its strategies of big data, and address a full range of potential organizational challenges. The strategic use of data must align with the business strategy of the organization, and embrace a long-term plan of strategy of business intelligence. A business organization's strategic intents encompass its managerial actions [15]. Nowadays the strategic intents of business organizations go beyond the traditional generic strategies (e.g., cost leadership, differentiation, niche marketing) to encompass IT innovations for hypercompetition. IT has become a type of commodity that makes business more productive than ever before. Mobile communication, the Internet, social media, and business management systems (e.g., ERP, CRM, and SCM systems) have been the basic tools of business operations. After decades of innovations in the IT industry, resistance to the adoption of IT is no longer a common issue in business organizations, but overuse of misuse of IT are widespread in many business organizations [67]. On the other hand, strategic use of data for data-driven decision making is often overlooked in the business society [52]. Advanced applications of big data require distinct knowledge and skills. To manage big data, the business organization must establish strategic plan for computing infrastructure, organizational procedures, policy, and rules relevant to big data [44].

Design Requirements

The business model of big data management of a firm is the design of requirements including the data contents, data sources, data collection, and data resource management functions. In the light of a profound impact of the big data wave, business intelligence and analytics is one of the emerging topics in the context of big data [55]. In its broad definition, business intelligence and analytics is a framework of practices for continuous iterative exploration and investigation of past business performance to gain insight and to drive business planning [7]. Given the breadth of the business intelligence and analytics, there are diversified design requirements of data sources and contents for big data management [25,31].

Business analytics can be a service of an enterprise information system of the organization, and the design of service-oriented system architecture for the organization is a prerequisite of effective business analytics for big data. Large-scale business analytics applications demand a redesign of database system infrastructure of the organization to improve the scalability and flexibility of the data management system [13,77].

Security, IT ethics, and intellectual properties related to big data are also important issues related to design of big data requirements for businesses [6]. Issues associated with data privacy, control, social and ethical concerns related to the way of exploiting big data can be a complex undertaking for a business. Computing policies, IT ethics code, intellectual property ownerships, and approaches to protecting the firm and customer information [39].

IT Solutions

The design of requirement drives to choose IT solutions to meet the challenge of big data. Advanced database applications, social media, open source software, open data sets, cloud computing, and development tools for business analytics and decision support systems are realistically feasible IT solutions.

A business needs to consider the most appropriate computing architecture for handling data-intensive applications, including hardware, computer networks, operating systems, database systems, and business analytics application software across the computer network. An effective and efficient decision making process must be supported by business intelligence and analytics tools. Traditional data processing and analysis tools may not be sufficient for big data. The IT industry and the research communities are making a great effort to define and to develop new generation tools for big data. In today's global economy, many businesses count on business intelligence and analytics practices to maintain or increase the business growth. For a business, the ultimate objective of dealing with big data is effective and efficient decision making.

Businesses are increasingly making use of social media tools to communicate with their customers, partners and vendors [57]. Diversified data can be collected by using social media. There are many challenges of the use of social media data including highly unstructured, noise, uncertain sources, etc. Social media analytics technologies are yet to come. Nevertheless, businesses can use different types of social networks to receive diversified strategic advices and entrepreneurial learning practices.

Cloud computing allows various platforms and networks to be used for businesses to store and to use big data which would otherwise require a large computing capacity [49,70]. Software as a service (SaaS) allows a business to have complete business applications in the cloud. Platform as a service (PaaS) can provide development tools for businesses to deal with big data in the cloud. Infrastructure as a service (IaaS) allows a business to build a system, including hardware, servers, data storage, and networking components, for dealing with big data.

As businesses have significant IT resource constraints, open source software is particularly practicable for business. Open source software products can be as powerful as competitive commercial products for data collection and processing. With the help of user communities on the Internet, a business is able to receive training or maintenance at affordable costs. Open government data sets are another free resource that can benefit businesses (e.g., [17]).

Outcome

Big data would not increase the market value of the organization automatically. The ultimate challenge of big data management is to generate business value from the explosion of big data. Business value of big data management can be generated from three aspects: transactional, informational, and strategic benefits [4,74]. Transactional value focused on business process efficiency and cost saving. Informational value stimulates data-driven timely decision making. Strategic value deals with gaining long-term strategic competitive advantages. The outcomes of big data resource management can be assessed by measuring the improvement of the efficiency of operational activities, quality of decision making, and the gain of long-term strategic benefits [62].

Causal Relationships between the Constructs

A good conceptual model about why and how IT affects organizations identifies the causal relationships between the constructs [46]. There are many types of causal relationships in IT-enabled business models [30,45]. In the present context of business model of big data resource management, causal relationships between the constructs represent the design of processes and actions, instead of explaining or predicting. Researchers in the IT management field commonly use subjective data to test conjectural causal relationships between constructs and often report inconsistent conclusions [26]. The present study is supported by observations of real-world business cases, and the factual evidences of causal relationships between the constructs warrant a generalization of the model.

The business model for big data resource management is depicted in Figure 3.

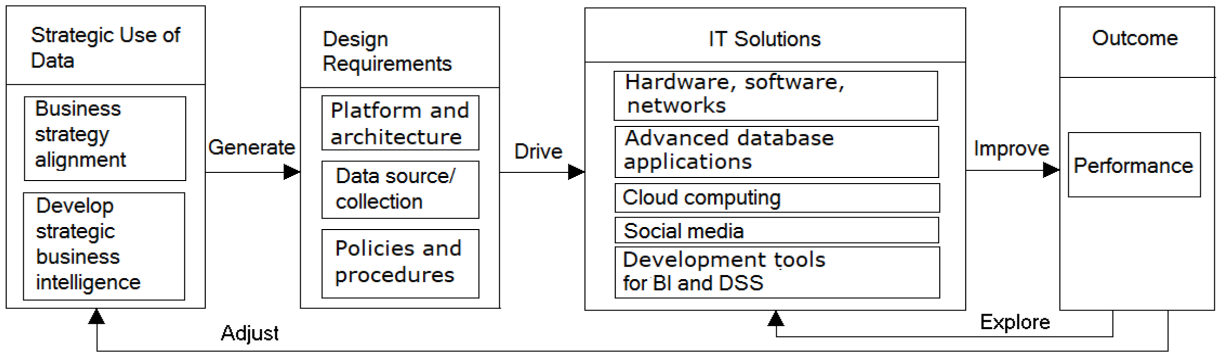

Figure 3: Conceptual Model of Effective Business Big Data Resource Management

DISCUSSION AND CONCLUSION

After years of big data innovations, the major tools on the software market used for big data in ordinary business organizations still depend on the relational database management systems instead of NoSQL databases. Hadoop technologies have been widely used to store big data, but they have not changed the fundamental database model and conventional business analytical approaches which are applied in ordinary business organizations. Despite the fast progress in both theory development and practice of big data, big data management is still developing, and conceptual models for big data management for business are needed for integrated business models for business organizations.

Managerial theories usually originate from business case studies [37]. This study applies a qualitative analysis approach to derive a conceptual model based on multiple cases. In comparison with common approaches to validation of conceptual models by using subjective survey data in the literature, the use of multiple business cases can ensure that the derived big data management model is consistent with the reality. The proposed model had included the key concepts of data resource management for business organizations. The proposed business model provides a framework for business to implement a comprehensive business model through big data resource management. It includes four constructs: strategic use of data, design of requirements, IT implementation, and outcome. These constructs are connected with causal relationships and form feedback loops. The feedback loops indicate the management control in big data resource management.

As the development of present conceptual model was based on the limited reported business cases of big data management, the study has its limitations. The number of cases used for the derivation of the business model is not large. The coding of these qualitative data could involve biases and errors. Consequently, the conceptual business model proposed in this paper is subject to further verification and validation. Independent empirical tests or independent case studies are needed for further testing of the proposed model. Future studies will improve the big data management business model.

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AUTHOR BIOGRAPHIES

Shouhong Wang is a Professor of Management Information Systems. He received his Ph.D. (1990) in Information Systems from McMaster University, Canada. His research interests include knowledge management and big data. He has published over 130 papers in academic journals, including *Journal of Information Technology Management, Journal of Management Information Systems, Information Systems Frontiers, Information & Management, International Journal of Information Management, Expert Systems with Applications, Information Systems Management, Journal of Electronic Commerce Research, IEEE Transactions on Systems, Man, and Cybernetics, Management Science, Decision Sciences, Information Resources Management Journal, Knowledge and Information Systems, Industrial Management and Data Systems,* and others.

Hai Wang is a Professor at the Sobey School of Business at Saint Mary's University, Canada. He received his B.Sc. in Computer Science from the University of New Brunswick, and his M.Sc. and Ph.D. in Computer Science from the University of Toronto. His research interests are in the areas of big data, knowledge management, and data mining. He has published over 80 papers in academic journals, including *Journal of Information Technology Management, VLDB Journal, IEEE Transactions on Systems, Man, and Cybernetics, Journal of Database Management, Knowledge and Information Systems, Managerial and Decision Economics, Performance Evaluation, Data & Knowledge Engineering, Expert Systems with Applications, Journal of Computer Information Systems,* and others.

APPENDIX A: CASES OF BUSINESS BIG DATA MANAGEMENT

Case No.	Case Title	Source	Brief Descriptions	Word Count
1	Crane Service, Inc. Using Mobile Tools for Heavy Lifting	Dalmas, R., Crane Service, Inc.: Using mobile tools for heavy lifting. https://bizcircle.att.com/real-stories/crane-services-inc-using-mobile-tools-for-heavy-lifting/#fbid=22w5XV1ivEH	Crane Service Inc. relies on mobile technology to keep their teamwork and instant communication in efficiency.	395
2	The University of Connecticut and VineSleuth	Gross, A., The University of Connecticut and VineSleuth http://ecc.ibm.com/case-study/us-en/ECCF-IMC15058USEN	VineSleuth's data model assesses wines objectively, by flavor alone. It asked IBM and the University of Connecticut to analyze how its results compare to data used by other wine industry leaders.	1668
3	Building financial datamart for smarter property management	Hsu, H., Hong Kong Housing Society optimizes financial reporting and planning with IBM Cognos. http://www-07.ibm.com/hk/e-business/case_studies/housing/index.html	Hong Kong Housing Society uses this big data to develop strategy, infuse intelligence in order to stay ahead of the technology revolution.	438
4	Reuters: Small business takes on big data	Sherwood, C. H., Small business takes on big data http://www.reuters.com/article/2013/02/04/us-data-smallbusiness-idUSBRE9130OT20130204	Startup companies uses the existing data model of the large companies to serve customers and improve their business through cost effective way.	1250
5	SAS: A prescription for cost effectively managing the chronically ill	SAS http://www.sas.com/en_is/customers/physicians-pharmacy-alliance.html	Reduction in medical costs of chronically ill patients can be controlled through medication care management program.	1348
6	How the big picture helps fight financial crime	SAS http://www.sas.com/en_us/customers/laurentian.html	Laurentian Bank of Canada uses three financial crime solutions implementing SAS in anti-money laundering, Fraud network analysis and enterprise case management using more than one channel, account or identity to pilfer money.	1076

7	Freezing out the issues	SAS http://www.sas.com/hu_hu/customers/sub-zero.html	Sub-Zero reduces the service indent rates by 50% while using analytics detecting strategy to identify emerging issues and solving them	1221
8	Consumers, Big Data, and Online Tracking in the Retail Industry: A case study of WALMART	Center for Media Justice https://saveballston.files.wordpress.com/2014/08/walmart_privacy_.pdf	Walmart tracks customers movement through their webcams, mobile wifi network, browsing history and share this data to about 50 clients for analysis.	701
9	Big data analytics and its application in e-commerce, case study of Adidas, Walmart, Amazon	Edosio, U., *Big data analytics and its application in e-commerce*, https://www.researchgate.net/publication/264129339_Big_Data_Analytics_and_its_Application_in_E-Commerce	Usage of big data analysis in providing a performance metric to assess the effectiveness in meeting customers' needs.	4455
10	Big data in big companies	Davenport, T. H. and Dyche, J., *Big data in big companies*, International Institute of Analytics, SAS Institute Inc., 2013. http://www.sas.com/resources/asset/Big-Data-in-Big-Companies.pdf	Case studies of Bank of America, Caesars Entertainment, United Healthcare, Macys, Sears, GE, Schneider National.	4969
11	Sam's club personalizes discounts for buyers	Martin, A., *Sam's club personalizes discounts for buyers*, The New York Times, 2010. http://www.nytimes.com/2010/05/31/business/31loyalty.html?pagewanted=all&_r=0	Determine optimum price for products and recommendation of similar products that the buyer might be interested to buy	1451
12	How customer analytics improve profitability?	Coleman, P., Mosiman, L., *How customer analytics improve profitability*, SAS Institute Inc. http://consumergoods.edgl.com/getmedia/680bc9d5-fb25-4885-96b3-c8505f2970b3/cgsm14_sas.pdf	Usage of customer historical data, variables of success prediction, and many more to improve profitability.	991
13	Data center trends - The 12 top ways data management will evolve in the 2010s	McKendrick, J., *Data center trends - The 12 top ways data management will evolve in the 2010s*, Jun 7, 2010. http://www.dbta.com/Editorial/Trends-and-Applications/Data-Center-Trends---The-12-Top-Ways-Data-Management-Will-Evolve-in-the-2010s-67590.aspx	Use of advanced, in-database analytics, enterprise-wide data integration, utility of enterprise data warehouse, alternate data warehouse, open source, semantic web for data management, are the major data management techniques in the industry.	3215
14	Evolving data center management and virtualization technologies drive cloud computing adoption	May, M., *Evolving data center management and virtualization technologies drive cloud computing adoption*, Sep 16, 2011. http://wwpi.com/evolving-data-center-management-and-virtualization-technologies-drive-cloud-computing-adoption/	Use of server virtualization technology reduces costs and increase agility and currently implemented in 70% of enterprises.	1509
15	Evolution from the Traditional Data Center to Exalogic	McDonald, R. et al., *Evolution from the traditional data center to Exalogic: an operational perspective, An oracle white paper*, July, 2012. http://www.oracle.com/us/products/middleware/exalogic/exalogic-operational-perspective-1723909.pdf	Use of Oracle Exalogic provides end to end integration, from the application layer to disk and thereby provides streamlined management.	2364

16	Turning Math into Cash	Bulkeley, W. M., Turning Math into Cash, Feb. 23, 2010. http://www.technologyreview.com/featuredstory/417595/turning-math-into-cash/page/2/	Brenda Dietrich head of mathematician global team helped IBM in generating 1 billion dollars in additional sales within 2 years by mathematical use of sales data.	2278

APPENDIX B: META-MATRIX (SIMPLIFIED VERSION)

Case No.	**Constructs of Business Model of Big Data Management for Business***								
	A	**B**	**C**	**D**	**AB**	**BC**	**CD**	**DA**	**DC**
1	1		2						
2	1	2	3	4	1	2	1	2	1
3	1		1	1			1		
4	1	2			1	1			
5	2	1	2	2	1	1		1	1
6	1	1	2	2	1	1	2	1	
7	2	1	1	2	1	1	1	2	
8	2	3	4	3	1	3	2	1	2
9	4	2	5	6	1	1	2	1	1
10	7	3	5	2	1		2	3	3
11	1		1	2				1	
12	2	2	2	3	2	1			
13	3	1	4	3	2	1	1	1	
14	3	8	1	3		2			
15	1	1	3	3	1	1	1	1	2
16	1		1	2		1		1	

* Notations corresponding to the conceptual model in Figure 3:
A: Strategic Use of Data
B: Design Requirement for Data Resource Management
C: IT Solution
D: Outcome
AB: Causal relation between Strategic Use of Data and Design Requirement of Data Resource Management
BC: Causal relation between Design Requirement of Data Resource Management and IT Solution
CD: Causal relation between IT Solution and Outcome
DA: Causal relation between Outcome and Strategic Use of Data
DC: Causal relation between Outcome and IT Solution