International Journal of Information Management 42 (2018) 78–89

Contents lists available at ScienceDirect

International Journal of Information Management

journal homepage: www.elsevier.com/locate/ijinfomgt

Big data with cognitive computing: A review for the future

Shivam Gupta[a], Arpan Kumar Kar[b,*], Abdullah Baabdullah[c], Wassan A.A. Al-Khowaiter[d]

[a] Montpellier Research in Management, Montpellier Business School, 2300 Avenue des Moulins, 34185, Montpellier, France
[b] Department of Management Studies, Indian Institute of Technology Delhi, Hauz Khas, New Delhi 110016, India
[c] Department of Management Information Systems, Faculty of Economics and Administration, King Abdulaziz University, Jeddah, Saudi Arabia
[d] Department of MIS and PM, Qassim University, Saudi Arabia

ARTICLE INFO

Keywords:
Big data
Cognitive computing
Literature review
Resource based View
Institutional theory

ABSTRACT

Analysis of data by humans can be a time-consuming activity and thus use of sophisticated cognitive systems can be utilized to crunch this enormous amount of data. Cognitive computing can be utilized to reduce the shortcomings of the concerns faced during big data analytics. The aim of the study is to provide readers a complete understanding of past, present and future directions in the domain big data and cognitive computing. A systematic literature review has been adopted for this study by using the Scopus, DBLP and Web of Science databases. The work done in the field of big data and cognitive computing is currently at the nascent stage and this is evident from the publication record. The characteristics of cognitive computing, namely observation, interpretation, evaluation and decision were mapped to the five V's of big data namely volume, variety, veracity, velocity and value. Perspectives which touch all these parameters are yet to be widely explored in existing literature.

1. Introduction

Advancement in technology has always been a natural phenomenon. Drastic technological advancements often tend to miss out to find itself a mass market where it can be sold. The population of the world stands at more than 7.4 billion people (Worldometers, 2016) and more than 3.1 billion of these people are connected to the internet (eMarketer Report, 2015). More than 4.4 billion people are using mobile phone, out of this 1.86 billion (42%) of people are using smart phone (eMarketer Report, 2015). The number of devices and connections will keep increasing year on year basis and thus this had led to an explosion of data (Yaqoob et al., 2016). This enormous amount of data that is produced on a continuous basis is termed as big data (Kreps & Kimppa, 2015). Fosso-Wamba et al. (2015) have discussed the concept of big data in detail and have brought out the various definitions by other researchers in this domain. Big data analytics has gained significant amount of importance as it enables organizations to be ahead of their competitors (Li, Tao, Cheng, & Zhao, 2015; Habib ur Rehman, Chang, Batool, & Wah, 2016; Bumblauskas, Nold, Bumblauskas, & Igou, 2017). Companies want to analyze this raw data as they want to spot the trends that they can use for further profit maximization (Frizzo-Barker, Chow-White, Mozafari, & Ha, 2016; Sun, Strang, & Firmin, 2016). The dire need to address the concerns of data deluge has led to the emergence of big data analytics (Dubey et al., 2015; Liberatore, Johnson, & Clain, 2016).

Analysis of data by humans can be a time-consuming activity and thus use of sophisticated cognitive systems can be utilized to crunch this enormous amount of data (Kim, Chan, & Gupta, 2016). Intel CEO Brian Krzanich explains in his editorial article on artificial intelligence (AI) in 2016 that *"AI is based on the ability of machines to sense, reason, act and adapt based on learned experience"* (Krzanich, 2016). In a system that is based on AI, it works on the rules and parameters that are fed inside it whereas a cognitive computing based system works by intercepting the command and then drawing inferences and suggesting possible solutions. Cognitive computing is an AI based system that enables it to interact with humans like a fellow human, interpret the contextual meaning, analyze the past record of the user and draw deductions based on that interactive session. Cognitive computing helps the humans in decision making whereas AI based systems works on the concept that machines are capable of making better decisions on the human's behalf. Cognitive computing is a sub-set of AI and anything that is cognitive is also AI.

The goal of cognitive computing is to build a rational, combined and collective mechanism motivated by the capability of human mind (Kwon, Lee, & Shin, 2014). Cognitive computing will develop unique learning systems, non-von Neumann computing structural design,

* Corresponding author.
E-mail addresses: connectwithshivamgupta@gmail.com (S. Gupta), arpan_kar@yahoo.co.in (A.K. Kar), baabdullah@kau.edu.sa (A. Baabdullah), w.alkhowaiter@gmail.com (W.A.A. Al-Khowaiter).

https://doi.org/10.1016/j.ijinfomgt.2018.06.005
Received 22 April 2018; Received in revised form 27 June 2018; Accepted 27 June 2018
0268-4012/

programming archetype and functions that can combine, examine and work on large volumes of data from variety of sources at once (Modha et al., 2011).

Raghupathi and Raghupathi (2014) have showcased the various sources that lead to generation of big data and it encompasses nearly every spectrum of academic and scientific domain. Cognitive computing can be utilized to reduce the shortcomings of the concerns faced during big data analytics (Hurwitz, Kaufman, & Bowles, 2015). In cognitive computing, a computerized model captures the human thought process and improvises on the mistakes the system commits every time (Modha et al., 2011). This self-learning mechanism can greatly benefit the way large amount of data is analyzed for better decision making (Gudivada, Raghavan, Govindaraju, & Rao, 2016). As there is an emergence in the implementation of cognitive computing to provide insights by analyzing large data sets, it is imperative to understand this subject matter.

The objectives of this literature review are:

- To propose a link between Cognitive Computing and Big Data.
- To perform a literature review and showcase the academic research work that has been published in the domain of Big Data and Cognitive Computing.
- To propose a conceptual model based on theoretical understanding to link the characteristics of Cognitive Computing by using the benefits offered by Big Data.

Section 2 showcases the background and motivation for this study. Section 3 brings out the methodology employed to undertake the literature review for big data and cognitive computing. Section 4 focusses on the analysis and discussion and Section 5 concludes this study with limitations and scope for future research. Appendix A in Table A1 shows the tabular representation of the journals and the years in which papers have been published. Appendix B presents a list of the selected papers that have been considered for the review.

2. Background and motivation

The history of computing is marked with events that very few had envisaged. The era of computing can be broadly classified into three categories:

2.1. The Tabulating Era (1900 s - 1940 s)

The computing devices consisted of calculators which were in the form of single-purpose mechanical systems where counting used to take place by using punched cards. The use of such systems was limited to large scale companies and academic and scientific institutions (IBM White Paper, 2015).

2.2. The Programming Era (1950 s - present)

During the World War II, the need for computing was driven by military and scientific requirements. Invention of transistor and the microprocessor lead to the creation of computers which were bulky machines compared to the modern day computer. The capacity and speed of the computer kept increasing at a drastic pace for the six decades and it has led to the creation of modern day compact computers to smart phones (IBM White Paper, 2015).

2.3. The Cognitive Era (2011 -)

The amount of data will become unsustainable for humans to process and thus there is a need for the computer systems to assist the humans in decision making (Changchit & Chuchuen, 2018). Having access to the vast amount of data will be a daunting task for any individual or an organization but a cognitive system can make sense of the raw data and turn into actionable information and thereafter valuable knowledge (IBM White Paper, 2015).

The origins of big data can be trailed back to the mid 1990′s when John Mashey, working at Silicon Graphics, USA was involved in processing and analysis of large datasets (Diebold, 2012). During a conference in 2010, Eric Schmidt, then Google CEO, had commented that the amount of data created in two days of time is equal to the amount of data created from the dawn of civilization till 2003 (Schmidt, 2010). This amount of data that he was referring was five Exabyte of data in 2010. Since then the amount of data created has only gone up exponentially. The ever-increasing challenges of data deluge have led to the rise of big data analytics (Raguseo, 2018). With more and more IoT (Internet of Things) connected devices, the problem of data deluge will further aggravate (Cintra White Paper, 2016; Hashem et al., 2016). Cognitive computing is considered to be a convergence of cognitive science, neuroscience, data science, and cloud computing (Gudivada et al., 2016). IBM has been pioneering in making commercial use of cognitive computing by launching Watson in 2011. There has been widespread of adoption of cognitive systems and the worldwide revenue for 2016 is touted at USD 8 billion and furthermore it is expected to rise to USD 47 billion by 2020 (IDC, 2016). The compound annual growth rate (CAGR) in this domain will be more than 55% over the five-year period from 2016 to 2020 (IDC, 2016). North America (the United States and Canada) constitute the biggest share (78%) in this USD 8 billion expected revenue and Europe, the Middle East and Africa (EMEA) comprise of the second largest region in the 2016 forecast of IDC. By 2020, the demand for cognitive systems from Asia-Pacific region including Japan will be similar to the EMEA region (IDC, 2016).

The intersection of mixed research studies using cognitive computing and big data analytics suffers from multiple challenges (Aswani, Kar, & Ilavarasan, 2017; Aswani, Ghrera, Kar, & Chandra, 2017). Cognitive computing approaches typically work on vectors having objective data where machine learning approaches learn through mathematical operations on these data. However, big data analytics can analyze and provide visualization of information in unstructured data (Ragini, Anand, & Bhaskar, 2018). The integration of these approaches first requires the conversion of unstructured data into some objective or quantitative parameters which are derived as vectors. Then these vectors over numerous instances may be used to train an algorithm in cognitive computing, so that predictions would be possible on the basis of the intent hidden in the content on test cases.

In order to extract the benefits of cognitive systems, it has to be fed with massive amount of data so that the systems are capable to find hidden patterns and relationships between the various variables which may be present in structured, semi-structured and unstructured data of high variety and veracity arriving in high volume and velocity. Thus, the field of big data analytics and cognitive computing will go hand-in-hand. The next section will highlight the methodology employed to undertake a literature review study for big data and cognitive computing as a combined subject matter.

3. Literature Review: Big Data and Cognitive Computing

The literature review for this study has been based on the guidelines that have been outlined by Tranfield, Denyer, and Smart, (2003) and Kitchenham and Charters (2007). There are three broad steps and they are namely: (i.) Planning the review, (ii.) Conducting the review and (iii.) Reporting the review. They are explained below:

3.1. Planning the Review

A review protocol has been developed that brings out the criterion for the selection of studies. The keywords that were used in this study were: **"big data"** and **"cognitive computing"**. An online digital database has been used to gather the information for the papers that are required for the review process. The digital databases that were

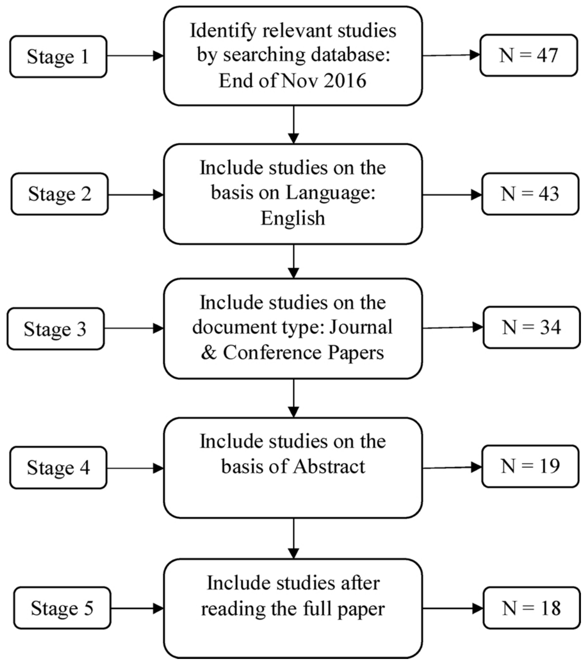

Fig. 1. Stages in Data Selection (Source: Authors' own compilation).

considered for this study are: (i.) Scopus, (ii.) Web of Science and (iii.) DBLP. Out of these three digital databases, first Scopus was considered for data extraction as: (i.) Maximum number of papers related to this study was indexed on Scopus compared to the other two digital databases, (ii.) It is the largest online database for peer-reviewed publications and (iii.) It has a broad overview of global and interdisciplinary scientific information. Web of Science and DBLP were also searched for papers and the papers that were not listed in Scopus, were included in the study as well. In Fig. 1, the various stages for data selection has been showcased.

3.2. Conducting the Review

The keywords used for selecting the research papers for this study and the search syntax are shown in Table 1.

The search syntax that is shown in Table 1 has been derived from the stages of data selection that can be seen in Fig. 1. The various attributes of Scopus search syntax are: (i.) TITLE-ABS-KEY: The selected keywords will be searched in the title, abstract and the keywords of the paper, (ii.) AND: And operator has been used which means that both the keywords should be present in the searched item, (iii.) LANGUAGE: Papers that have been written in English are considered in this study, (iv.) LIMIT-TO(DOCTYPE): Only journal and conference papers were considered for the review in this study. Here, 'ar' stands for journal article, 'cp' stands for conference paper, 're' stands for review papers and 'ip' stands for journals papers that are in-press. The search syntax for Web of Science and DBLP can be easily comprehended and understood from Table 1. The search was conducted in the end of Nov 2016.

Table 2
Document Type per Year.

Document TypeYear	2016	2015	2014	2013	Total	%
Conference Paper	2	3	1		6	33%
Journal Paper	5	5	1	1	12	67%
Total	7	8	2	1	18	

3.3. Reporting the Review

A total of 44 papers were showcased on Scopus, 9 papers were listed on Web of Science and 3 papers were showcased on DBLP with the selected keywords. Only one paper listed in Web of Science and two papers showcased in DBLP were not part of the Scopus search result. After filtering the search result for only papers that are written in English language, a total of 43 papers were left. As this study only considers journal and conference papers, the search result was reduced to 34 papers. Abstract of all the 31 papers from Scopus, 1 paper from Web of Science and 2 papers from DBLP, was available on these three online digital databases and it was used to screen out the papers that were not relevant for this study. This leads to a further reduction in the number of papers to 19. All these 19 papers were downloaded and after reading the papers, it was found that 18 of these papers are relevant for this review study. The details of these 18 papers can be seen in Appendix A Table A1. In Table 2, a breakdown of these 18 papers can be seen. It can be observed that the academic output in this field of research is in its nascent stage and there has been emphasis on this topic since 2015. Two-thirds of the publications were journal papers (Table 2).

As these digital databases presents a broad overview of the academic and scientific development in all the spheres of research, the papers considered for this study also showcases this spectrum. Fig. 2 shows the documents by subject area.

Table 3 highlights the major keywords that were present in these 18 papers based on number of occurrences in each manuscript.

Table 4 showcases the documents by country and international collaboration. It can be seen that there has been only one case of international collaboration in this subject matter. Majority of the countries listed in Table 4 have an overall high percentage of international collaboration (Source: SJR Country Rankings, 2015). International collaborative work can lead to diffusion of ideas and development on the research topic is a much faster manner (Adams, Gurney, & Marshall, 2007; European Commission Report, 2009). As this field of study is nascent, the academic research output also lacks any international collaboration.

Out of the 18 selected papers, only three authors have more than one paper: (i.) Garrett, M.A. (Netherlands), (ii.) Sengupta, P.P. (United States) and (iii.) Sheth, A. (United States).

Table 1
Search Syntax on Online Digital Databases.

Data Source: End of Nov 2016	Search Syntax
Scopus Database: (https://www.scopus.com) Keyword used: **"big data"** and **"cognitive computing"**	(TITLE-ABS-KEY("big data") AND TITLE-ABS-KEY("cognitive computing")) AND (LIMIT-TO (LANGUAGE,"English")) AND (LIMIT-TO(DOCTYPE,"ar") OR LIMIT-TO(DOCTYPE,"cp") OR LIMIT-TO (DOCTYPE,"re") OR LIMIT-TO(DOCTYPE,"ip"))
Web of Science Database: (https://apps.webofknowledge.com) Keyword used: **"big data"** and **"cognitive computing"**	TOPIC: ("big data") AND TOPIC: ("cognitive computing") Refined by: LANGUAGES: (ENGLISH) AND DOCUMENT TYPES: (ARTICLE OR REVIEW) Timespan: All years. Indexes: SCI-EXPANDED, SSCI, A&HCI, ESCI.
DBLP Database: (http://dblp.uni-trier.de/search) Keyword used: **"big data"** and **"cognitive computing"**	"big data" "cognitive computing"

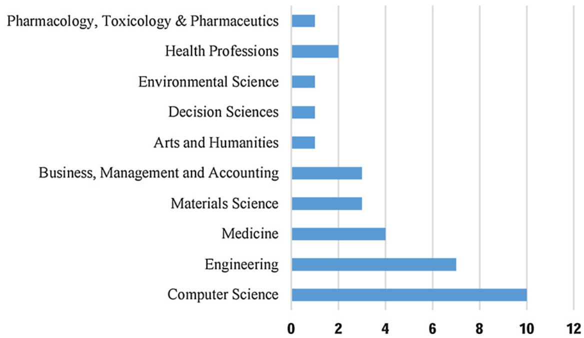

Fig. 2. Documents by Subject Area (Source: Authors' own compilation).

Table 3
Presence of Other Keywords in the Papers.

Keyword	No. of Papers
Cognitive Computing	16
Big Data	13
Cognitive Systems	5
Internet	5
Artificial Intelligence	3
Data Analytics	3

Table 4
Documents by Country and International Collaboration.

Country	No. of Papers	Intl. Coll. in this study	Overall % of Intl. Coll. in these Countries (2015)
United States	10.5	1 Paper	34%
Netherlands	2	No	58%
Canada	1	No	50%
China	1	No	21%
India	1	No	16%
Italy	1	No	45%
Thailand	1	No	43%
UK	0.5	1 Paper	52%
Total	**18**		

4. Analysis and Discussion

There have been big changes in the field of computer science technology. Modern intelligent computing can process voluminous data at superfast speed. Intelligent computing is influenced by a number of factors such as (i) changing technologies, smart devices, sensors; (ii) increasing technological complexity that can process data faster; (iii) research studies on human machine interaction and its abilities.

Cognitive computing can examine a range of various types of data and its interpretation to generate rich insights (Ogiela & You, 2013). Cognitive computing comprises various tools and techniques such as Big Data and Predictive analytics; IoT; Machine Learning; Natural Language Processing; Causal Induction; Probabilistic Reasoning and Data Visualization. Interestingly, cognitive systems have the ability to learn, remember, and analyze a problem which is contextually relevant to the firm. Some of the key features of a cognitive system are: learning ability and improving knowledge without reprogramming; develop and analyze hypotheses based on the system's current knowledge base.

Significant symbiosis between big data and cognitive computing is basically the availability of huge volume of data which is immensely useful for the types of machine learning and methods on which cognitive computing provides appropriate solutions. Cognitive computing scores over the technologies employed for big data analytics in three aspects; namely; scalability, dynamism, and natural interaction. In cognitive computing, hypotheses are formed which are formulated as well as tested and based on the results gathered, the system can improvise on the existing hypotheses. This attribute brings the estimation and the thinking process as close to humans as possible. Since, the number of redundant calculations involved are reduced, the whole process is scalable as it saves time and efforts. As data is being generated on a regular basis, it is possible that some new variables may come up which are not part of the original model that is being tested. In big data analytics, model adjustments have to be done manually whereas in cognitive computing, the system can incorporate such changes on its own and even compare the analysis with prior tested results. This situation wherein the content is evolving and the system can incorporate such dynamic changes on its own showcases the dynamism of the cognitive computing over big data analytics. Synthesis of natural language is a significant implication which makes cognitive computing highly desirable. This capability to process unstructured data and natural language within shorter time duration as compared to big data analytics brings out the natural interaction aspect. However, the situation is not so promising as there are limitations of cognitive computing. A cognitive system has a limited understanding of the risk as this may not be part of the structured or unstructured data. For instance, a cognitive system can recommend the country for investment in the government linked project but it may not factor in socio-economic conditions like change in the government due to elections. A cognitive system needs to undergo extensive amount of training to understand the data, context, process and to develop an understanding so that with every iteration, the system becomes more robust. The efficacy of a cognitive system needs to be established when there is high level of uncertainty in terms of data sources and/ or drastic and sudden changes in the context of the situation.

Firms can use the potential of cognitive computing systems in handling the issues while extracting key business insights from the voluminous data. The output of the big data analytics can be food for thought for the systems based on cognitive computing. However in order to understand the working of a system based on cognitive computing, it is important to analyze the way humans indulge in decision making process. These processes can be classified as: (i.) observation, (ii.) interpretation, (iii.) evaluation and (iv.) decision (Chen, Argentinis, & Weber, 2016).

Every moment data generated from business operations need to be captured, sorted, prepared and analyzed for effective decision making. However, managing the big data is a challenge in front of management researchers and managers primarily due to large amount of data; high speed of data generation and delivery; different sources of big data; quality of big data and trustworthiness of sources.

The factors that are required for the successful implementation of big data analytics have been categorized as 5V's: (i.) volume, (ii.) variety, (iii.) velocity, (iv.) veracity and (v.) value (Bedeley, Ghoshal, Iyer, & Bhadury, 2016; Demirkan et al., 2015; Dwivedi, Janssen et al., 2017; Fosso-Wamba et al., 2015; Grover & Kar, 2017). The characterization of both cognitive computing and big data that have been listed above are related to each other (Hurwitz et al., 2015). Resource Based View (RBV) theory advocates the need of VRIN framework (Valuable, Rare, Inimitable and Non-substitutable) for an enterprise to have competitive advantage over their competitors (Barney, 1991; Abu Bakar & Ahmad, 2010; Qi & Chau, 2013). The capability of a firm to effectively manage the characteristics of big data (5V's) by use of cognitive computing can enable an organization in creation of new value that can further improve the efficiency and competitiveness of the enterprise (adapted from Daft, 1983; Mousavizadeh, Ryan, Harden, & Windsor, 2015; Ong & Chen, 2016). A conceptual model has been proposed that showcases cognitive computing can be utilized to better understand the complexity of data deluge (Fig. 3). The data can be in the form of unstructured, structured and semi-structured that has the distinct VRIN features that are reflected by the 5V's of this big data. Cognitive Informatics (Wang, 2009) and Social Cognitive Theory (Bandura, 1986; Dwivedi, Rana, Jeyaraj, Clement, & Williams, 2017) advocates that a cognitive system involves an interaction between

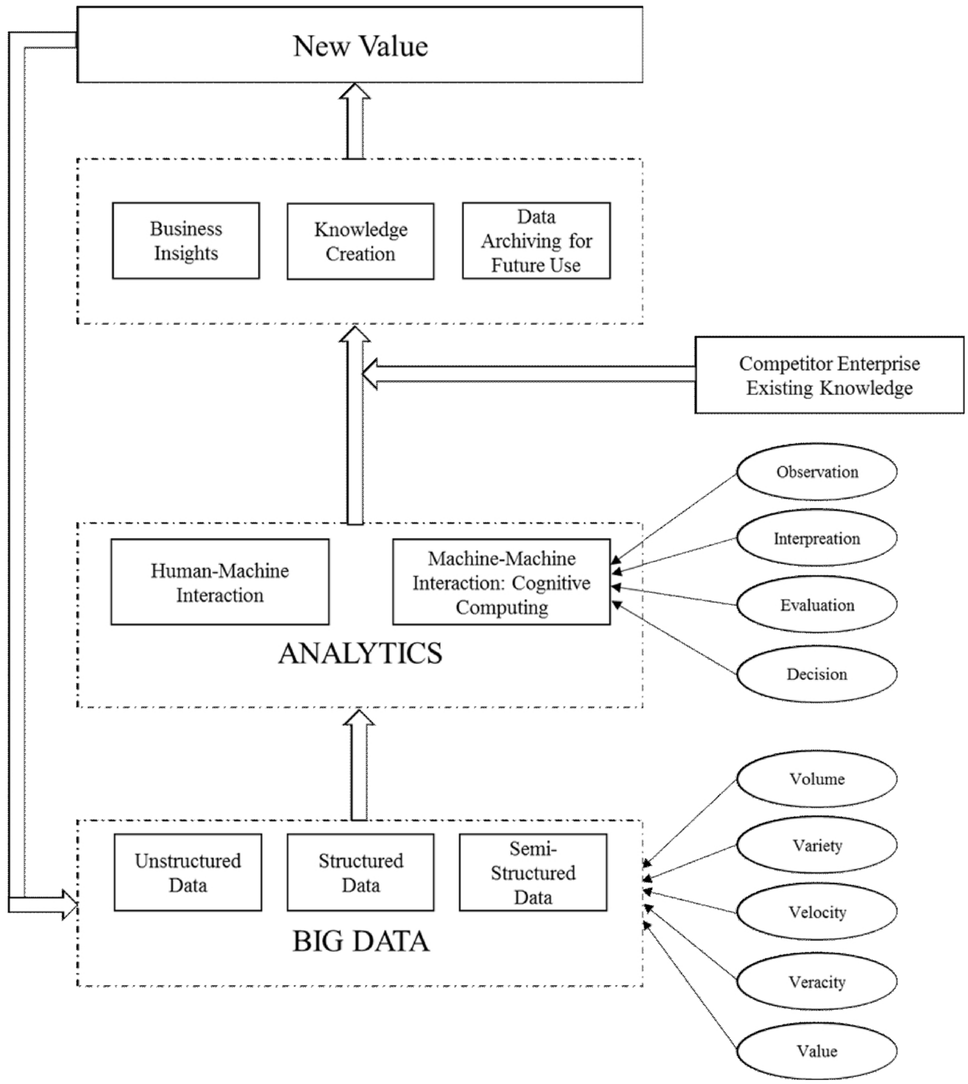

Fig. 3. Conceptual Model Relating Big Data and Cognitive Computing (Source: Authors' own compilation).

machine to machine where the system learns from the mistakes it commits. With every iteration, this system becomes more efficient in better understanding the patterns and thereby leading to minimum human intervention. Oliver (1997) and DeVaujany, Carton, Mitev, and Romeyer, (2014) have highlighted the case of combining the RBV with the insights of the institutional theory. In this conceptual model (Fig. 3), we have extended RBV theory by use of mimetic isomorphic driver of the institutional theory of DiMaggio and Powell (1983). The works of Mignerat and Rivard (2009) and Weerakkody, Dwivedi, and Irani, (2009) has shown that institutional theory is instrumental in shaping the work in the domain of information systems. We postulate that coercive or normative pressures (part of Institutional Theory) may not be compelling for an enterprise to envisage the use of cognitive computing in analyzing the challenges involved in understanding the complexity of big data. As every organization now strives to be technologically advanced, peer pressure can be a compelling factor for enterprises to imitate the path undertaken by their competitors (Aerts, Cormier, & Magnan, 2006). This process can lead an enterprise to stay abreast with the advancement in technology so that more and more meaningful insights can be gathered for effective decision making. Thus, in Fig. 3, it can be seen that existing enterprise knowledge of successful competitors can help an organization to also replicate their path of success (Chevallier, Laarraf, Lacam, Miloudi, & Salvetat, 2016; Zanzouri & Francois, 2013). The knowledge that is created can have a positive impact on the organizational performance which can further impose pressure on their competitors for enhanced performance (Dubey, Gunasekaran, Angappa, & Papadopoulos, 2017; Grover & Kohli, 2012). The new value that is created by making sense out of data that was earlier discarded as there was no ways and means to process it can further fuel growth for an organization (Hung, Chia-An, Tsai, Lee, & Chau, 2015; Zhan, Tan, Ji, Chung, & Tseng, 2017).

This inter-linkage of the characteristics of big data and cognitive computing can be seen below:

Observation of data is the basic requirement for a cognitive system where aggregation, integration and examination of data takes place (Chen et al., 2016). For a cognitive system to make observations, it should have access to volumes of data. **Volume** is the amount of data that is generated, stored and managed for data analysis. The advent of social web and interconnected devices has led to the emergence of large amount of data (Batty, 2012; Kapoor et al., 2018). This data can either be structured or unstructured data and a cognitive system would normalize and cleanse the data into a particular format for further analysis. The challenge of data deluge can be effectively countered by use of cognitive systems as humans will find it increasingly tough to make observations in such a large amount of data.

Interpretation of datasets will yield in better understanding and solving of complex set of problems when there is variety of information sources. The data can be in the form of structured, unstructured, image,

Table 5
Mapping of Characteristics of Cognitive Computing and Big Data.

Cognitive Computing	Observation	Interpretation	Evaluation	Decision
Big data	Volume	Variety	Velocity	Veracity

text, multimedia and also there can be cases of missing data (Santos et al., 2017). This **variety** of data can be sourced from various avenues like social media, IoT devices, RFID (Radio Frequency Identification) devices, emails, GPS (Global Positioning System) devices and so on (Bertino et al., 2011). For a cognitive system to learn and interpret; it has to be supplied with a variety of data and thereafter the system will be capable of interpreting the data on its own by understanding the contextual meaning of the subject matter (Chen et al., 2016). In order to keep abreast with the developments in the field of science, humans have to constantly update their existing knowledge base from the various possible sources of information. Cognitive systems can bridge this gap and assist humans in gaining insights.

Evaluation of data to generate information to answer a query is part of the natural ability in a human being. A cognitive system converts the raw data it gathers into visual networks of data which leads to creation of many relationships within the data. The process of processing this huge amount of data requires the cognitive system to be able to perform this within a very short time frame. **Velocity** is an attribute of big data where it is important to monitor the rate at which data is generated and at the same time it is also concerned with the speed with which this data is processed (Hurwitz et al., 2015). At the same time it is essential to bring efficacy in data analysis so that the evaluation is trustworthy and accurate (Gandomi & Haider, 2015). **Veracity** is a characteristic of big data where it deals with foreseeing the quality, uncertainty and trustworthiness of the data (Demirkan et al., 2015). For a cognitive system to evaluate the data, it is essential for the system to perform this task in a timely, trustworthy and an accurate manner.

Decision refers to the capability of the cognitive system to make decisions based on the data that has been analyzed. One of the major criteria for decision making is availability of evidence and a cognitive system heavily relies on evidence-based decision making. A cognitive system employs use of quantitative predictive analytics for decision making when there is lack of clear-cut evidence (Chen et al., 2016). This reduces the mistakes made by humans when they tend to rely on guesswork and trial and error. **Value** as a characteristic of big data suggests that the large volume of data is worthless until the data is converted to knowledge (Jara, Genoud, & Bocchi, 2014; Saberi, Hussain, & Chang, 2017). This process can also lead to data repurposing that can be processed and analyzed further for knowledge creation (ICO Report, 2014). This value may be realized in different contexts of big data usage, like smart cities, social media, user generated content and search engines (Alalwan, Rana, Dwivedi, & Algharabat, 2017; Aswani, Kar, Ilavarasan, & Dwivedi, 2018; Chauhan, Agarwal, & Kar, 2016; Rathore, Kar, & Ilavarasan, 2017; Saumya, Singh, Baabdullah, Rana, & Dwivedi, 2018).

Based on the discussion on the various facets of cognitive computing and big data, it is observed that the factors that determine the capability of a cognitive system can be mapped to the factors for successful implementation of big data analytics (Table 5).

In this study, the selected papers have been evaluated on the basis of their coverage of the factors that have been listed in Table 5. If the author(s) have highlighted these factors from the perspective of both cognitive computing and big data, then it is considered to be included in Table 6. As the five V's of the big data have been explicitly explained and used in the academic literature, they have been used in Table 6. Table 6 shows the mapping of the selected 18 papers with the characteristics exhibited by big data and cognitive computing.

From the above table, it is evident that all the five aspects of big data and four aspects of cognitive computing have been represented by the papers. The major emphasis of all the papers has been on creating value from data to information to knowledge to wisdom. Extracting the benefits of big data and cognitive computing will lead an organization to scale-up the DIKW Pyramid (Jifa & Lingling, 2014). In order to have a transition from data to wisdom in this data intensive age which is also known as the Fourth Research Paradigm, e-Research can equip the academic and scientific community with the tools and technologies for data mining, data visualization and data dissemination (Hey, Tansley, & Tolle, 2009; Lloyd, Antonioletti, & Sloan, 2016). A key benefit of e-Research lies in the potential of solving the challenge of data deluge by indulging in collaborative research as the existing data can be easily accessed, reused and shared for data analysis and repurposing (Jirotka,

Table 6
Mapping of the Selected Papers.

		Big Data					Cognitive Computing			
S.No.	Authors	Volume	Variety	Velocity	Veracity	Value	Observation	Interpretation	Evaluation	Decision
1	Chen et al., 2016	1	1	1	1	1	1	1	1	1
2	Coccoli et al., 2016	1	1	1		1	1	1	1	
3	Demirkan et al., 2015	1	1	1	1	1	1	1	1	1
4	Garrett, 2015	1			1	1	1	1	1	
5	Garrett, 2014	1	1	1	1	1	1	1	1	
6	Hensley, 2014			1		1	1	1	1	
7	Khatri and Shrivastava, 2016	1	1	1	1	1	1	1	1	1
8	Lie et al., 2015	1	1				1	1	1	
9	Maymir-Ducharme et al., 2015	1	1	1	1	1	1	1	1	1
10	Noor, 2015	1	1	1	1	1	1	1	1	1
11	Robson and Boray, 2015	1	1	1	1	1	1	1	1	
12	Sengupta, 2013	1	1	1	1	1	1	1	1	1
13	Sengupta et al., 2016	1	1	1	1	1	1	1	1	1
14	Sheth, 2016	1	1	1	1	1	1	1	1	1
15	Sheth et al., 2016	1	1			1	1	1	1	1
16	Smit, 2016	1	1	1	1	1	1	1	1	
17	Spohrer and Banavar, 2015	1	1	1	1	1	1	1	1	1
18	Van De Bogart, 2015	1	1	1		1	1	1	1	

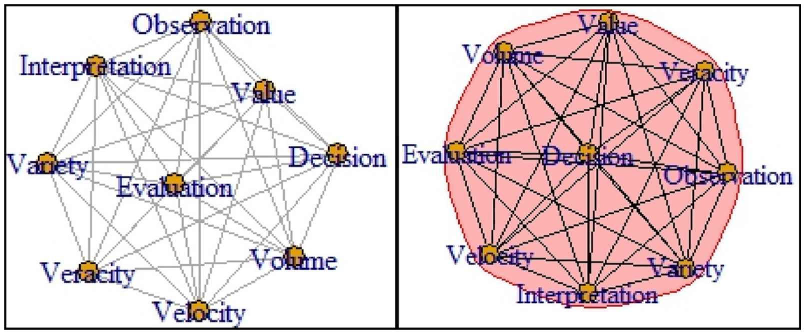

Fig. 4. (a) and Fig. 4(b): Community analysis within focus areas.

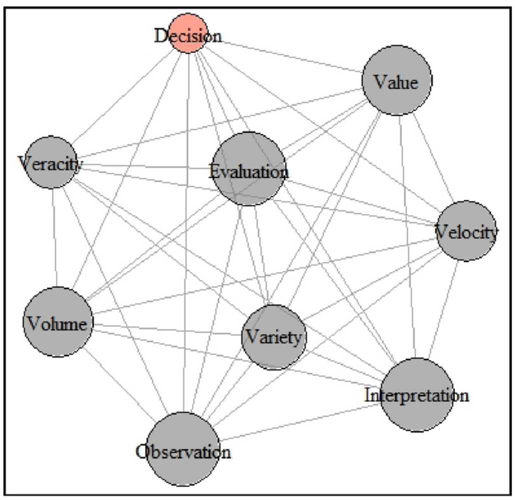

Fig. 5. Community outlier detection.

Lee, & Olson, 2013). In Table 4, it can be seen that as of now there has been hardly any international collaboration on this subject matter. The selected papers have strongly suggested that cognitive computing can be instrumental in utilizing the benefits of big data analytics and also to address the challenge faced by the same. Further an attempt to explore the nature of linkages between these characteristics of big data and cognitive computing was attempted using network analysis.

Fig. 4(a) illustrates the network association of five V's; volume, variety, velocity, veracity and value; related to big data and four factors of cognitive computing such as observation, interpretation, evaluation and decision. Each node represents the charateristic. The edges within the factors are drawn on the basis of the co-occurrence of the factors within in the research articles. On the network of the Fig. 4(a), Newman–Girvan community detection algorithm (Newman, 2012) was applied. The community detection algorithm finds the community among the big data factors and cognitive computing factors on the basis of the edge betweeness in association matrix. The outcome of the algorithm is presented in Fig. 4(b). Fig. 4(b) illustrates all the factors are closely related and the occurrence of the factors are occurring frequently in nature together based on what the studies ideate on.

However, when the actual coverage of these studies were explored an interesting observation emerged. On the network of the Fig. 4(a), community detection based on greedy optimization of modularity (Su, Kuchinsky, Morris, States, & Meng, 2010) was applied. The outcome of the algorithm is presented in Fig. 5. The size of the sphere of the factors in Fig. 5 depicts its frequency of occurrences in the research article. Using this algorithm, two communities have been identified. The first community consists of only one factor that is decision factor belonging to cognitive computing (represented using the pink color in Fig. 5). The second community consists of other eight factors represented using the grey nodes. Fig. 5 depicts five V's are tightly coupled leading to observation, interpretation and evaluation but still facing problems in taking decision related tasks. This outlier indicates that for future academic explorations, studies should focus on decisions when exploring any problem statement within this domain.

In Table 7, the attributes of the selected papers can be seen where the focus has been on the interdependence of big data and cognitive computing.

From the existing papers, it can be inferred that the domain of cognitive computing has been instrumental in capturing the benefits of big data analytics and this can be seen in the real world in the field of healthcare sector (Table 7). IBM Watson has been highly cited in these selected papers and 13 out of the 18 papers have highlighted the benefits of how cognitive computing enabled IBM Watson is using big data for better decision making. The success of using cognitive technologies for big data analytics in the healthcare sector will pave the path for this to be implemented in other spheres of life (Lahtiranta, Koskinen, Knaapi-Junnila, & Nurminen, 2015). Also, the field of astronomy has been witnessing the emergence of employing cognitive systems coupled with the power to extract information out of big data (Garrett, 2014 and Garrett, 2015).

5. Conclusion

This paper provides an analysis of the existing academic literature in the domain of big data and cognitive computing. In this study, we have followed the approach of systematic literature review and we have used digital databases like Scopus, Web of Science and DBLP to extract the information.

The knowledge base on big data analytics and cloud computing has been extended by some notable research studies such as (Irani, Ghoneim, & Love, 2006, 2017; Lal & Bharadwaj, 2016; Sivarajah, Kamal, Irani, & Weerakkody, 2017).

The broad challenges of big data can be grouped into three main categories, based on the data life cycle: data, process and management challenges (Sivarajah et al., 2017).

Verma and Bhattacharyya (2017) found that the major reason behind big data analytics non-adoption is that the firms do not realize the strategic value of big data analytics. Firm managers are also not prepared to bring the changes because of technological, organizational and environmental difficulties.

On the other side relative advantage, security concern, top management support, technology readiness, competitive pressure and

Table 7
Big Data and Cognitive Computing Attributes.

S.No.	Attribute	Big Data and Cognitive Computing	Study (Appendix B) and Source
1	Expediting the discovery in the field of Life Sciences Research	"Cognitive computing on large unstructured datasets could accelerate discovery of relationships between biological entities for which there was yet no explicit evidence of their existence."	Chen et al., 2016 (Scopus)
2	Impact on the learning processes and the labor market	"It is compulsory that knowledge is generated and managed in a better way and, consequently, the new professionals should require different skills. The solution relies in the new wave of cognitive computing systems, which are going to change everything."	Coccoli et al., 2016 (Scopus)
3	Role of Big Data and Cognitive Computing in IoT devices	"Business and societal systems are instrumented (sensors), interconnected (data stored in the cloud and accessible from mobile devices), and intelligent (cognitive systems can provide customers with high-quality recommendations and help customers make better data-driven decisions), we can say that business and societal systems are getting smarter."	Demirkan et al., 2015 (Scopus)
4	Role of Big Data and Cognitive Computing in Astronomical Research	"Faced with an avalanche of data from all sides, the “brute force” approach of commercial data analytics, and especially the future promise of cognitive computing, could have a huge impact in terms of increasing the chances of serendipitous discovery."	Garrett, 2015 (Scopus)
5	Role of Big Data and Cognitive Computing in Astronomical Research	"Applying cognitive computing to large astronomical surveys could have a huge impact in terms of serendipitous discovery - areas that might specifically benefit include those like SETI where human bias and other pre-conceptions may limit current efforts."	Garrett, 2014 (Scopus)
6	Use of IBM Watson in solving the challenges of Big Data	"IBM Watson offers the next generation of cognitive computing that helps bring understanding to big data. And data warehousing and big data are headed in that direction."	Hensley, 2014 (Scopus)
7	Use of Cognitive Computing to solve the issues of Big Data in Healthcare Industry	"The major challenge in medical field is to make smarter decisions at right time from very large volume of structured and unstructured data coming from heterogeneous sources. These data can be de-identified, shared and combined with the frequently increasing observation of clinical, research and social health data (in a secure and private environment) via cloud computing. IBM Watson offers cognitive computing powers to be applied to the stored data."	Khatri and Shrivastava, 2016 (Scopus)
8	Cognitive Computing is not effective for analysis of Big Data	"The existing cognitive concept learning algorithms are not very effective for large data although they are relatively acceptable."	Li et al., 2015 (DBLP)
9	Use of Cognitive Computing to tackle the concerns of Big Data in Healthcare Industry	"Applying text and data mining techniques, pattern recognition, and cognitive computing techniques on large volumes of clinical and genomic data, smarter health informatics and analytics can drive knowledge discovery that have a direct impact on patients at the point of care."	Maymir-Ducharme et al., 2015 (Scopus)
10	Potential of Cognitive Computing and role of Big Data	"With the advent of big data, which grows larger, faster and more diverse by the day, cognitive computing systems are now used to gain knowledge from data as experience and then generalize what they have learned in new situations."	Noor, 2015 (Scopus)
11	Implementation of inference system in the domain of medicine by using data from various sources	"The user can currently propose inference nets and refine them with the help of the system, based on what is available, and on viable replacements. It would seem that some basic expertise in probability, statistics and inference is required. Indeed, there now seems to be a major task ahead, the complete automation of generating the best choice of inference network from the very beginning."	Robson and Boray, 2015 (Scopus)
12	Use of Cognitive Computing and Big Data for Disease Assessment	"As more and more data become available, the challenge will be how to mine the vast datasets to facilitate and expedite decision making. One of the steps in meeting this challenge could be to develop cognitive tools for automated analysis of big functional datasets."	Sengupta, 2013 (Scopus)
13	Use of Cognitive Computing for pattern recognition in Big Data in the Healthcare Industry	"Complex pattern recognition in big data is better performed using machine approaches, a potential solution to meet this challenge is to develop computer-based cognitive tools for automated analysis."	Sengupta et al., 2016 (Scopus)
14	Role of Big Data and Cognitive Computing in IoT devices	"Cognitive computing acts as prosthetics for human cognition by analyzing a massive amount of data and being able to answer questions humans might have when making certain decisions."	Sheth, 2016 (Scopus)
15	Semantic, Perceptual, and Cognitive Computing with Big Data	"CC (Cognitive Computing) has garnered substantial recent interest and provides the ability to utilize relevant knowledge and help improve the understanding of data for decision-making, and is seeing rapid technological progress."	Sheth et al., 2016 (Scopus)
16	Emphasis on Converged Reality with Cognitive Computing and Big Data	"The use of appropriate tools – records management, data analytics, cognitive computing – can mitigate the impact, but given the volume, variety (lack of, or varied, structure), and velocity (rate of new data being created) of Big Data, existing techniques fall short."	Smit, 2016 (Scopus)
17	Emphasis on Cognitive Computing as a Service from the Perspective of Industry	"Cognition as a service can help unlock the mysteries of big data and ultimately boost the creativity and productivity of professionals and their teams, the productive output of industries and organizations, as well as the GDP (gross domestic product) of regions and nations."	Spohrer and Banavar, 2015 (Web of Science)
18	Development of Cognitive Systems using Big Data	"The real challenge that confronts the entire global IT community and the one that is causing advances in quantum computing, cognitive architectures and artificial general intelligence is how the exponential rise in data can be converted into usable information."	Van De Bogart, 2015 (Scopus)

trading partners' pressure were found as the critical drivers of cloud computing adoption (Lal & Bharadwaj, 2016)

The review of prior literature shows that the domain of big data has been fairly explored but the domain of cognitive computing is in its nascent stages of development. As there has been an explosion in creation of data and thereby it is virtually impossible for a human to kept a tab on all the latest developments for decision making process.

The domain of cognitive computing will be incomplete without harnessing the benefits of big data analytics. A conceptual model based on the learning drawn from RBV theory (Barney, 1991) and mimetic isomorphic driver of the institutional theory (DiMaggio & Powell, 1983) has been proposed in this study that needs to be tested and verified to validate this model. The theoretical foundations of cognitive computing can be found in Cognitive Informatics and Social Cognitive Theory (SCT). Cognitive Informatics (Wang, 2009) is a trans-disciplinary research domain that addresses the challenges to mimic the human thought process by sharing the domain knowledge of the various engineering and social-science disciplines. SCT (Bandura, 1986) emphasizes on the reciprocal interactions between the environment and the behavior of an individual on his/ her cognitive perceptions. SCT has been instrumental in the development of the computing technology. Cognitive systems are capable in capturing the human thought process and thereafter learning from the mistakes when the system commits them. This is evident from the offerings of IBM Watson where the system is revolutionizing the healthcare industry by providing medical insights to doctors in better decision making. The system gathers information from all possible electronic means and filters the relevant information which can be considered for real-time decision making. This service is made available to doctors by diffusing the information through cloud-based network thereby reducing the cost of implementing such a system even at a small-scale level. If the service offerings of cognitive computing are limited to organizations where installation of IT infrastructure is mandatory, then this service will remain exclusive to the large enterprises only. It is a business decision for companies that provide cognitive computing services to either cater for the masses or the classes. A mixed approach can also be employed to tap the market at all levels. In this study it is seen that the major emphasis has been in the healthcare sector where IBM Watson has revolutionized the medical practices of doctors. Employing the benefits of cognitive computing and big data will lower the cost of services incurred to the user in the long run as this system will reduce the human intervention.

As cognitive computing is increasing its reach, big data analytics will fuel its growth into an exponential manner to become an integral part of the human life. The key findings for researchers from this study are:

1 The work done in the combined field of big data and cognitive computing is at a nascent stage and this is evident from the publication record. From 2013, there is a presence of academic literature in this combined field but the emphasis has been from the year 2015.
2 There has been hardly any international collaboration so far. There is a need for international collaborations to bring out the contexts and trade-offs between localization versus globalization through cognitive computing in such research explorations.
3 The major emphasis of this combined field is in the healthcare sector. 13 out of the 18 selected papers have brought out the benefits of IBM Watson. For practice, this provides an immense chance to explore and document the value of cognitive computing and big data analytics through application-oriented research.
4 The characteristics of cognitive computing with regards to the five V's of big data are: (i.) observation, (ii.) interpretation, (iii.) evaluation and (iv.) decision. These characteristics are critical for future explorations in the domain to realize the complete value from big data applications. This is still yet to be explored extensively in existing literature which however touches upon the 5 Vs of big data analytics.
5 The interface of big data analytics and cognitive computing is yet to focus on the implications of the studies on decision making. The network analysis highlights that decision is a node which is yet to be touched extensively in such studies. This again is a direction towards a missing link (namely focus on decision making), for realizing the true value of the applications and explorations in this domain.

5.1. Managerial Implications

The key takeaways for managers are as under:

The quality of data is vital for harnessing cognitive computing and providing the right solution and recommendation for the business problem. Change management is important in any medium to large range organization for exploiting big data management under cognitive computing. Upgrading knowledge, skills and abilities of human resources are equally important for sustainability. Cognitive systems are going to bring a big change in the future business platform and will help to produce more innovations and new product developments under the influence of internal and external pressures. However, care must be taken from safety, security and sustainability perspective to reduce the associated risks.

5.2. Limitations and Future Research Directions

The limitation of this study is that the academic literature that individually exists in the domain of big data and cognitive computing was not included in this study. It is possible that papers written in these individual scientific fields could possess information that could be valuable for this study. If such studies did not match the search criteria, they may have been omitted. As it can be seen from this study that the publications in this field has garnered attention from 2013 and thus this opens up many future research opportunities. The characteristics of big data and cognitive computing (shown in Table 5) can be utilized to better understand the concerns of trust, privacy and information security. As healthcare sector has seen the first implementation of cognitive systems using benefits of big data analytics, it paves the path for this to be replicated in other paradigms of scientific as well as industrial domains. IBM Watson has indeed been successful in the domain of healthcare but it has expanded to other domains like advertising, customer engagement, education, financial services, IoT, media and much more where it is working with leading companies to make smarter decisions. Dispersion of the benefits offered by big leaps in technology like cognitive computing and big data analytics can be a key challenge for small and medium enterprises (SMEs). SMEs do not have the financial bandwidth that is required to use such technology and the technical know-how along-with trained manpower is critical as well. Thus, future studies focusing on how use of cognitive computing coupled with big data analytics can be brought to the table of SMEs will be of great importance. One such possible way is to make use of cloud computing. Earlier use of enterprise resource planning (ERP) was restricted to large enterprises only but with the coming of cloud based ERP services, it is no longer a niche product. Researchers can explore the possibility on how cloud computing can act as a faster medium for the mass use of cognitive computing and big data analytics.

Appendix A

Table A1
Source Title per Year.

Source Title	2013	2014	2015	2016	Total
Acta Astronautica			1		1
Advances in Intelligent Systems and Computing				1	1
AI Magazine			1		
Circulation: Cardiovascular Imaging				1	1
Clinical Therapeutics				1	1
Communications of the Association for Information Systems			1		1
Computer				1	1
Computers in Biology and Medicine			1		
HEALTHINF 2015 - 8th International Conference on Health Informatics, Proceedings; Part of 8th International Joint Conference on Biomedical Engineering Systems and Technologies, BIOSTEC 2015			1		1
IBM Data Management Magazine		1			1
IEEE Intelligent Systems				1	1
IOP Conference Series: Materials Science and Engineering		1			1
JACC: Cardiovascular Imaging	1				1
Journal of Visual Languages and Computing				1	1
Open Engineering			1		1
Proceedings of the Annual Hawaii International Conference on System Sciences				1	1
Proceedings of the International Conference on Intellectual Capital, Knowledge Management and Organisational Learning, ICICKM			1		1
Proceedings of the International Conference on Machine Learning and Cybernetics (ICMLC)			1		
Total	**1**	**2**	**8**	**7**	**18**

Appendix B

Papers Considered for this study

Chen Y., Argentinis E. and Weber G. (2016), "IBM Watson: How Cognitive Computing Can Be Applied to Big Data Challenges in Life Sciences Research," *Clinical Therapeutics*, Vol. 38 No. 4, pp. 688–701.

Coccoli M., Maresca P., Stanganelli L. (2016), "The role of big data and cognitive computing in the learning process", *Journal of Visual Languages and Computing*.

Demirkan H., Bess C., Spohrer *J*., Rayes A., Allen D. And Moghaddam Y. (2015), "Innovations with smart service systems: Analytics, big data, cognitive assistance, and the internet of everything", *Communications of the Association for Information Systems*, Vol. 37 No. 1, pp. 733–752.

Garrett M.A. (2015), "SETI reloaded: Next generation radio telescopes, transients and cognitive computing", *Acta Astronautica*, Vol. 113, pp. 8–12.

Garrett M.A. (2014), "Big Data analytics and cognitive computing-future opportunities for astronomical research," *IOP Conference Series: Materials Science and Engineering*, Vol. 67 No. 1.

Hensley N. (2014), "Data warehousing: The brains of the big data operation", IBM Data Management Magazine.

Khatri I., Shrivastava V.K. (2016), "A survey of big data in healthcare industry", *Advances in Intelligent Systems and Computing*, Vol. 452, pp. 245–257.

Li, *J*., Huang, C., Xu, W., Qian, Y. and Liu, W. (2015), "Cognitive concept learning via granular computing for big data", International Conference on Machine Learning and Cybernetics (ICMLC), 2, pp. 289–294.

Maymir-Ducharme F.A., Angelelli L. and Rao P. (2015), "Smarter healthcare built on informatics and cybernetics," HEALTHINF 2015 - 8th International Conference on Health Informatics, Proceedings; Part of 8th International Joint Conference on Biomedical Engineering Systems and Technologies, BIOSTEC 2015, pp. 525–533.

Noor A.K. (2015), "Potential of cognitive computing and cognitive systems", *Open Engineering*, Vol. 5 No. 1, pp. 75–88.

Robson B., Boray S. (2015), "Implementation of a web based universal exchange and inference language for medicine: Sparse data, probabilities and inference in data mining of clinical data repositories", *Computers in Biology and Medicine*, Vol. 66, pp. 82–102.

Sengupta P.P. (2013). "Intelligent platforms for disease assessment: Novel approaches in functional echocardiography", *JACC: Cardiovascular Imaging*, Vol. 6 No. 11, pp. 1206–1211.

Sengupta P.P., Huang Y.-M., Bansal M., Ashrafi A., Fisher M., Shameer K., Gall W. and Dudley *J*.T. (2016), "Cognitive Machine-Learning Algorithm for Cardiac Imaging; A Pilot Study for Differentiating Constrictive Pericarditis from Restrictive Cardiomyopathy," *Circulation: Cardiovascular Imaging*, Vol. 9 No. 6.

Sheth A. (2016), "Internet of Things to Smart IoT Through Semantic, Cognitive, and Perceptual Computing", *IEEE Intelligent Systems*, Vol. 31 No. 2, pp. 108–112.

Sheth A., Anantharam P. and Henson C. (2016), "Semantic, cognitive, and perceptual computing: Paradigms that shape human experience," *Computer*, Vol. 49 No. 3, pp. 64–72.

Smit M. (2016), "Converged reality: A data management research agenda for a service-, cloud-, and data-driven era," *Proceedings of the Annual Hawaii International Conference on System Sciences*, 2016-March, pp. 1653–1662.

Spohrer, *J*. and Banavar, G. (2015), "Cognition as a Service: An Industry Perspective," *AI Magazine*, Vol. 36 No. 4, pp. 71–86.

Van De Bogart W. (2015), "Information entanglement: Developments in cognitive based knowledge acquisition strategies based on big data," Proceedings of the International Conference on Intellectual Capital, Knowledge Management and Organisational Learning, ICICKM, 2015-January, pp. 299–307.

References

Abu Bakar, L. J., & Ahmad, H. (2010). Assessing the relationship between firm resources and product innovation performance: A resource based view. *Business Process Management Journal, 16*(No. 3), 420–435.

Adams, J., Gurney, K., & Marshall, S. (2007). *Patterns of international collaboration for the UK and leading partners (Summary report)*. Evidence Ltd. - A Report Commissioned by the UK Office of Science and Innovation.

Aerts, W., Cormier, D., & Magnan, M. (2006). Intra-industry imitation in corporate environmental reporting: An international perspective. *Journal of Accounting and Public Policy, 25*(No. 3), 299–331.

Alalwan, A. A., Rana, N. P., Dwivedi, Y. K., & Algharabat, R. (2017). Social media in marketing: A review and analysis of the existing literature. *Telematics and Informatics, 34*(No. 7), 1177–1190.

Aswani, R., Kar, A. K., Ilavarasan, P. V., & Dwivedi, Y. K. (2018). Search engine marketing is not all gold: Insights from twitter and SEOClerks. *International Journal of Information Management, 38*(No. 1), 107–116.

Aswani, R., Ghrera, S. P., Kar, A. K., & Chandra, S. (2017). Identifying buzz in social media: A hybrid approach using artificial bee colony and k-nearest neighbors for outlier detection. *Social Network Analysis and Mining, 7*(No. 1), 38.

Aswani, R., Kar, A. K., & Ilavarasan, P. V. (2017). Detection of spammers in twitter marketing: A hybrid approach using social media analytics and bio inspired computing. *Information Systems Frontiers,* 1–16.

Bandura, A. (1986). *social foundations of thought and action: A social cognitive theory.* Englewood Cliffs, NJ, USA: Prentice-Hall.

Barney, J. B. (1991). Firm resources and sustained competitive advantage. *Journal of Management, 17*(No.1), 99–120.

Batty, M. (2012). Smart cities, Big data. *Environment and Planning B: Planning and Design, 39*(No. 2), 191–193.

Bedeley, R. T., Ghoshal, T., Iyer, L. S., & Bhadury, J. (2016). Business analytics and organizational value chains: A relational mapping. *Journal of Computer Information Systems*. http://dx.doi.org/10.1080/08874417.2016.1220238.

Bertino, E., Bernstein, P., Agrawal, D., Davidson, S., Dayal, U., Franklin, M., Gehrke, J., Haas, L., Halevy, A., & Han, J. (2011). *"Challenges and opportunities with Big data", a community white paper developed by leading researchers across the United States*.

Bumblauskas, D., Nold, H., Bumblauskas, P., & Igou, A. (2017). Big data analytics: Transforming data to action. *Business Process Management Journal, 23*(No. 3), http://dx.doi.org/10.1108/BPMJ-03-2016-0056.

Changchit, C., & Chuchuen, C. (2018). Cloud computing: An examination of factors impacting users' adoption. *Journal of Computer Information Systems, 58*(No 1), 1–9. http://dx.doi.org/10.1080/08874417.2016.1180651.

Chauhan, S., Agarwal, N., & Kar, A. K. (2016). Addressing big data challenges in smart cities: a systematic literature review. *INFO, 18*(No. 4), 73–90.

Chen, Y., Argentinis, E., & Weber, G. (2016). IBM watson: How cognitive computing can Be applied to Big data challenges in life sciences research. *Clinical Therapeutics, 38*(No. 4), 688–701.

Chevallier, C., Laarraf, Z., Lacam, J. S., Miloudi, A., & Salvetat, D. (2016). Competitive intelligence, knowledge management and coopetition: The case of European high-technology firms. *Business Process Management Journal, 22*(No. 6), 1192–1211.

Cintra White Paper (2016). *Information lifecycle management.* Cintra Version 1.0.

Daft, R. L. (1983). *Organization theory and design.* NewYork: West Publishing Co.

Demirkan, H., Bess, C., Spohrer, J., Rayes, A., Allen, D., & Moghaddam, Y. (2015). Innovations with smart service systems: Analytics, big data, cognitive assistance, and the internet of everything. *Communications of the Association for Information Systems, 37*(No. 1), 733–752.

DeVaujany, F. X., Carton, S., Mitev, N., & Romeyer, C. (2014). Applying and theorizing institutional frameworks in IS research. *Information Technology & People, 27*(No. 3), 280–317.

Diebold, F. (2012). *A personal perspective on the origin(s) and development of 'big data': The phenomenon, the term, and the discipline.* USA: University of Pennsylvania.

DiMaggio, P. J., & Powell, W. W. (1983). The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields. *American Sociological Review, 48*(No. 2), 147–160.

Dubey, R., Gunasekaran, A., & Papadopoulos, T. (2017). Green supply chain management: Theoretical framework and further research directions. *Benchmarking: An International Journal, 24*(No 1), 184–218.

Dubey, R., Gunasekaran, A., Childe, S. J., Fosso-Wamba, S., et al. (2015). The impact of big data on world-class sustainable manufacturing. *The International Journal of Advanced Manufacturing Technology, 84*(No. 1), 631–645.

Dwivedi, Y. K., Janssen, M., Slade, E. L., Rana, N. P., Weerakkody, V., Millard, J., Hidders, J., & Snijders, D. (2017). Driving innovation through big open linked data (BOLD): Exploring antecedents using interpretive structural modelling. *Information Systems Frontiers, 19*(No 2), 197–212.

Dwivedi, Y. K., Rana, N. P., Jeyaraj, A., Clement, M., & Williams, M. D. (2017). Re-examining the unified theory of acceptance and use of technology (UTAUT): Towards a revised theoretical model. *Information Systems Frontiers,* 1–16. http://dx.doi.org/10.1007/s10796-017-9774-y.

eMarketer Report (2015). *Worldwide internet and Mobile users: eMarketer's updated estimates for 2015.* eMarketer.

European Commission Report (2009). *Drivers of International collaboration in research*Brussels, Belgium: Directorate-General for Research, European Commission.

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

Frizzo-Barker, J., Chow-White, P. A., Mozafari, M., & Ha, D. (2016). An empirical study of the rise of big data in business scholarship. *International Journal of Information Management, 36*(No 3), 403–413.

Gandomi, A., & Haider, M. (2015). Beyond the hype: Big data concepts, methods, and analytics. *International Journal of Information Management, 35*(No 2), 137–144.

Garrett, M. A. (2014). Big data analytics and cognitive computing-future opportunities for astronomical research. *IOP Conference Series: Materials Science and Engineering, 67*(No. 1), 1–4.

Garrett, M. A. (2015). SETI reloaded: Next generation radio telescopes, transients and cognitive computing. *Acta Astronautica, 113*, 8–12.

Grover, P., & Kar, A. K. (2017). Big data analytics: A review on theoretical contributions and tools used in literature. *Global Journal of Flexible Systems Management, 18*(No. 3), 203–229.

Grover, V., & Kohli, R. (2012). Cocreating it value: New capabilities and metrics for multiform environments. *MIS Quarterly, 1*, 225–232 Vol. 36.

Gudivada, V. N., Raghavan, V. V., Govindaraju, V., & Rao, C. R. (2016). *Cognitive computing: Theory and applications* (1st edition). North Holland Publisher.

Habib ur Rehman, M., Chang, V., Batool, A., & Wah, T. Y. (2016). Big data reduction framework for value creation in sustainable enterprises. *International Journal of Information Management, Part A, 36*(6), 917–928.

Hashem, I. A. T., Chang, V., Anuar, N. B., Adewole, K., Yaqoob, I., Gani, A., Ahmed, E., & Chiroma, H. (2016). The role of big data in smart city. *International Journal of Information Management, 36*(No. 5), 748–758.

Hey, S., Tansley, S., & Tolle, K. (2009). *The fourth paradigm: Data-intensive scientific Discovery.* Washington, USA: Microsoft Research, Redmond.

Hung, S. Y., Chia-An, Tsai, J., Lee, W. T., & Chau, P. Y. K. (2015). Knowledge management implementation, business process, and Market relationship outcomes: An empirical study. *Information Technology & People, 28*(No. 3), http://dx.doi.org/10.1108/ITP-12-2013-0209.

Hurwitz, J. S., Kaufman, M., & Bowles, A. (2015). *Cognitive computing and Big data analytics.* Indianapolis, Indiana, USA: John Wiley & Sons, Inc.

IBM White Paper (2015). *Computing, cognition and the future of knowing: How humans and machines are forging a new age of understanding.* New York, USA: IBM Research and Solutions Portfolio, IBM Global Services.

ICO Report (2014). *Big data and data protection*UK: Information Commissioner's Office Version: 1.0.

IDC (2016). *Worldwide semiannual cognitive/artificial intelligence systems spending guide.* International Data Corporation (IDC).

Irani, Z., Ghoneim, A., & Love, P. E. (2006). Evaluating cost taxonomies for information systems management. *European Journal of Operational Research, 173*(No. 3), 1103–1122.

Irani, Z., Sharif, A. M., Lee, H., Aktas, E., Topaloğlu, Z., van't Wout, T., et al. (2017). Managing food security through food waste and loss: Small data to big data. *Computers & Operations Research,* 1–17. http://dx.doi.org/10.1016/j.cor.2017.10.007.

Jara, A. J., Genoud, D., & Bocchi, Y. (2014). *Big data in smart cities: From Poisson to human dynamics. Proceedings of the 28th International Conference on Advanced Information Networking and Applications Workshops (WAINA)*785–790.

Jifa, G., & Lingling, Z. (2014). Data, DIKW, Big data and data science. *Procedia Computer Science, 31*, 814–821.

Jirotka, M., Lee, C. P., & Olson, G. M. (2013). Supporting scientific collaboration: Methods, tools and concepts. *Computer Supported Cooperative Work, 22*, 667–715.

Kapoor, K. K., Tamilmani, K., Rana, N. P., Patil, P., Dwivedi, Y. K., & Nerur, S. (2018). Advances in social media research: Past, present and future. *Information Systems Frontiers, 20*(No 3), 531–558.

Kim, H. W., Chan, H. C., & Gupta, S. (2016). Examining information systems infusion from a user commitment perspective. *Information Technology & People, 29*(No. 1), 173–199.

Kitchenham, B. A., & Charters, S. M. (2007). *Guidelines for performing systematic literature reviews in software engineering*Version 2.3. EBSE Technical Report EBSE-2007-01. Keele University and Durham University.

Kreps, D., & Kimppa, K. (2015). Theorising web 3.0: ICTs in a changing society. *Information Technology & People, 28*(No. 4), 726–741.

Krzanich, B. (2016). *The intelligence revolution – Intel's AI commitments to deliver a better world.* Web-LinkEditorial, Intel Newsroomhttps://newsroom.intel.com/editorials/krzanich-ai-day/.

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

Lahtiranta, J., Koskinen, J. S. S., Knaapi-Junnila, S., & Nurminen, M. (2015). Sensemaking in the personal health space. *Information Technology & People, 28*(No. 4), 790–805.

Lal, P., & Bharadwaj, S. S. (2016). Understanding the impact of cloud-based services adoption on organizational flexibility: An exploratory study. *Journal of Enterprise Information Management, 29*(No. 4), 566–588.

Li, J., Tao, F., Cheng, Y., & Zhao, L. (2015). Big data in product lifecycle management. *The International Journal of Advanced Manufacturing Technology, 81*(No. (1-4)), 667–684.

Liberatore, M. J., Johnson, B. P., & Clain, S. H. (2016). Analytics capabilities and the decision to invest in analytics. *Journal of Computer Information Systems*. http://dx.doi.org/10.1080/08874417.2016.1232995.

Lloyd, A. D., Antonioletti, M., & Sloan, T. M. (2016). Able but not willing? Exploring divides in digital versus physical payment use in China. *Information Technology & People, 29*(No. 2), 250–279.

Mignerat, M., & Rivard, S. (2009). Positioning the institutional perspective in information systems research. *Journal of Information Technology, 24*(No. 4), 369–391 Special Issue on Institutional Theory in Information, London.

Modha, D. S., Ananthanarayanan, R., Esser, S. K., Ndirango, A., Sherbondy, A. J., & Singh, R. (2011). Cognitive computing. *Communications of the ACM, 54*(No. 8), 62–71.

Mousavizadeh, M., Ryan, S., Harden, G., & Windsor, J. (2015). Knowledge management and the creation of business value. *Journal of Computer Information Systems, 55*(No. 4), 35–45.

Newman, M. E. (2012). Communities, modules and large-scale structure in networks. *Nature Physics, 8*(No. 1), 25–31.

Ogiela, M. R., & You, I. (2013). Cognitive and secure computing in information management. *International Journal of Information Management, 33*(No 2), 243–244.

Oliver, C. (1997). Sustainable competitive advantage: Combining institutional and resource based views. *Strategic Management Journal, 18*(No. 9), 697–713.

Ong, C.-S., & Chen, P.-Y. (2016). A valuation model for information technology capability-enabled firm value. *Journal of Computer Information Systems, 56*(No. 2), 137–144.

Qi, C., & Chau, P. Y. K. (2013). Investigating the roles of interpersonal and interorganizational trust in IT outsourcing success. *Information Technology & People, 26*(No. 2), 120–145.

Raghupathi, W., & Raghupathi, V. (2014). Big data analytics in healthcare: Promise and potential. *Health Information Science and Systems, 2*(No. 3), 1–10.

Ragini, J. R., Anand, P. M. R., & Bhaskar, V. (2018). Big data analytics for disaster response and recovery through sentiment analysis. *International Journal of Information Management, 42*, 13–24.

Raguseo, E. (2018). Big data technologies: An empirical investigation on their adoption, benefits and risks for companies. *International Journal of Information Management, 38*(No 1), 187–195.

Rathore, A. K., Kar, A. K., & Ilavarasan, P. V. (2017). Social media analytics: Literature review and directions for future research. *Decision Analysis, 14*(No. 4), 229–249.

Saberi, M., Hussain, O. K., & Chang, E. (2017). Past, present and future of contact centers: A literature review". *Business Process Management Journal, 23*(No. 3), 574–597. http://dx.doi.org/10.1108/BPMJ-02-2015-0018.

Santos, M. Y., Oliveira e Sá, J., Andrade, C., Vale Lima, F., Costa, E., Costa, C., Martinho, B., & Galvão, J. (2017). A Big data system supporting Bosch Braga industry 4.0 strategy. *International Journal of Information Management, 37*(No 6), 750–760.

Saumya, S., Singh, J. P., Baabdullah, A. M., Rana, N. P., & Dwivedi, Y. K. (2018). Ranking online consumer reviews. *Electronic Commerce Research and Applications, 29*(May–June), 78–89.

Schmidt, E. (2010). *Every 2 days we create as much information as we did up to 2003.* TechCrunch.

Sivarajah, U., Kamal, M. M., Irani, Z., & Weerakkody, V. (2017). Critical analysis of Big data challenges and analytical methods. *Journal of Business Research, 70*, 263–286.

Su, G., Kuchinsky, A., Morris, J. H., States, D. J., & Meng, F. (2010). GLay: Community structure analysis of biological networks. *Bioinformatics, 26*(No. 24), 3135–3137.

Sun, Z., Strang, K., & Firmin, S. (2016). Business analytics- based Enterprise information systems. *Journal of Computer Information Systems*. http://dx.doi.org/10.1080/08874417.2016.1183977.

Tranfield, D., Denyer, D., & Smart, P. (2003). Towards a methodology for developing evidence: Informed management knowledge by means of systematic review. *British Journal of Management, 14*, 207–222.

Verma, S., & Bhattacharyya, S. S. (2017). Perceived strategic value-based adoption of Big data analytics in emerging economy: A qualitative approach for Indian firms. *Journal of Enterprise Information Management, 30*(No. 3), 354–382.

Wang, Y. (2009). Formal description of the cognitive process of memorization. *Transactions of Computational Science V, 5540*, 81–98 of the series Lecture Notes in Computer Science.

Weerakkody, V., Dwivedi, Y. K., & Irani, Z. (2009). The diffusion and use of institutional theory: A cross-disciplinary longitudinal literature survey. *Journal of Information Technology, 24*(No. 4), 354–368.

Worldometers (2016). *Current world population.* Last accessed on Dec 03, 2016http://www.worldometers.info/world-population/.

Yaqoob, I., Hashem, I. A. T., Gani, A., Mokhtar, S., Ahmed, E., Anuar, N. B., et al. (2016). Big data: From beginning to future. *International Journal of Information Management, 36*(6), Part B), 1231–1247.

Zanzouri, C., & Francois, J. C. (2013). Knowledge management practices within a collaborative R&D project: Case study of a firm in a cluster of railway industry. *Business Process Management Journal, 19*(No. 5), 819–840.

Zhan, Y., Tan, K. H., Ji, G., Chung, L., & Tseng, M. (2017). A big data framework for facilitating product innovation processes. *Business Process Management Journal, 23*(No. 3), http://dx.doi.org/10.1108/BPMJ-11-2015-0157.