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Big data applications in operations/supply-chain management: A literature review

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ABSTRACT

Purpose: Big data is increasingly becoming a major organizational enterprise force to reckon with in this global era for all sizes of industries. It is a trending new enterprise system or platform which seemingly offers more features for acquiring, storing and analysing voluminous generated data from various sources to obtain value-additions. However, current research reveals that there is limited agreement regarding the performance of "big data." Therefore, this paper attempts to thoroughly investigate "big data," its application and analysis in operations or supply-chain management, as well as the trends and perspectives in this research area. This paper is organized in the form of a literature review, discussing the main issues of "big data" and its extension into "big data II"/IoT–value-adding perspectives by proposing a value-adding framework.
Methodology/research approach: The research approach employed is a comprehensive literature review. About 100 or more peer-reviewed journal articles/conference proceedings as well as industrial white papers are reviewed. Harzing Publish or Perish software was employed to investigate and critically analyse the trends and perspectives of "big data" applications between 2010 and 2015.
Findings/results: The four main attributes or factors identified with "big data" include – big data development sources (Variety – V_1), big data acquisition (Velocity – V_2), big data storage (Volume – V_3), and finally big data analysis (Veracity – V_4). However, the study of "big data" has evolved and expanded a lot based on its application and implementation processes in specific industries in order to create value (Value-adding – V_5) – "Big Data cloud computing perspective/Internet of Things (IoT)". Hence, the four Vs of "big data" is now expanded into five Vs.
Originality/value of research: This paper presents original literature review research discussing "big data" issues, trends and perspectives in operations/supply-chain management in order to propose *"Big data II" (IoT – Value-adding) framework*. This proposed framework is supposed or assumed to be an extension of "big data" in a value-adding perspective, thus proposing that "big data" be explored thoroughly in order to enable industrial managers and businesses executives to make pre-informed strategic operational and management decisions for increased return-on-investment (ROI). It could also empower organizations with a value-adding stream of information to have a competitive edge over their competitors.

1. Introduction

Data has increased on a large scale in various fields over the last two decades; hence, the term "big data" has been coined. It has been largely anticipated that the amount of data will continue to increase greatly in the coming years in this digital era, where huge amounts of data are constantly being generated from several sources. A report from International Data Corporation (IDC), Gantz and Reinsel (2011) indicates that the overall created and copied data volume in the world was 1.8ZB (≈ 1021B), which increased by nearly nine times within a five year period. The world generated over 1ZB of data in 2010, and by 2014 7ZB per year (Richard, Matthew, & Carl, 2011). A great amount of this data increase is the result of diverse devices employed at the periphery of industrial enterprise supply chain (SC) networks including embedded sensors, smartphones, computer systems and computerized devices. All of this data creates new opportunities to extract more value. Therefore, "big data" could be defined as a fast-growing amount of data from various sources that increasingly poses a challenge to industrial organizations and also presents them with a complex range of valuable-use, storage and analysis issues. Current research on "big data" reveals that there is limited

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agreement regarding the most valuable use or performance of "big data" in industrial operations and neither is there even a single agreed definition of it. Attempts to compare traditional datasets with big data typically include masses of unstructured data that needs more real-time analysis. Furthermore, big data is also believed to enable new opportunities to discover new value-adding and make strategic decisions that would help industrial enterprises to gain a better understanding of the hidden values of "big data" and also rise to new challenges, e.g. how to effectively organize, manage or store and analyse such datasets.

Industrial enterprises as well as governmental and parastatal institutions such as ministries *(e.g., of finance, health care, telecommunications, immigration, education, agriculture, etc.)* have recently become keenly interested in the high value-adding potential of big data. Hence, many government agencies have initiated major plans to accelerate big data research and applications (Report to the President Big Data and Privacy: A Technological Perspective, 2014). Big data research has also gained a lot popularity in the academic world, which has motivated publications from a lot of publishing houses as well as congress and conference proceeding themes in addition to the media and industrial white papers. Therefore, the impact, performance and challenges of big data have been discussed widely across all the various sectors. However, big data is still seen as an abstract concept; thus, differentiating between itself and "huge data" or "massively big data" is still rather fuzzy. Although the essence of big data value-adding has been generally acknowledged, industrial enterprise managers still have different opinions on its definition mainly relative to the nature of their operations. Big data could generally be referred to as the datasets that could not be perceived, acquired, managed or stored and finally analysed by legacy IT and software/hardware systems within a reasonable time frame. Thus, various stakeholders have their own definition of big data which are most likely relative to the nature of their organizational operations.

According to Min, Shiwen, and Yunhao (2014), big data typically comprises masses of unstructured data that needs more real-time analysis. Manyika et al. (2011) defined big data as the next frontier for innovation, competition, and productivity (Intel IT Centre – Peer Research, 2012). Richard et al. (2011) in their IDC whitepaper stated that big data technology could be described as a new generation of technologies and architectures, designed so that enterprise organizations could economically extract value from very large volumes of a wide variety of data by enabling high-velocity capture, discovery, storage and analysis. This definition is largely agreed to by many researchers and enterprise industrial R&D managers (Seref and Duygu, 2013; Min et al., 2014; Manyika et al., 2011; Janusz, 2013), although it is also obvious others have different views. The IDC, one of the most influential leaders in big data and its research fields, defines big data in two of its reports (Gantz & Reinsel, 2011; Richard et al., 2011), and outlines some attributes of big data as the four Vs, that is, big data development sources (Variety – V_1), big data acquisition (Velocity – V_2), big data storage (Volume – V_3), big data analysis (Veracity – V_4), and finally modulating towards big data value adding or implementation benefits to industry (Value-adding – V_5). Hence, the five Vs of big data can be seen in Fig. 1, which illustrates the big data S-cure. This implies that big data is thus the data of which the data volume, acquisition speed or data representation limits the capacity of using classical database management methods to conduct effective analysis (Mayer-Schönberger & Cukier, 2013) and therefore that efficient methods or technologies need to be developed and used to analyse and process big data.

The S-curve model in Fig. 1 illustrates the need to scrutinize the attributes of big data for a more optimum value-adding approach by squeezing a huge data volume (V_3) for more enhanced data flow velocity (V_2) into a lesser time, and also stepping up the data variety (V_1) into a more enhanced date veracity (V_4) in a lesser time. According to Hauang, Zhong, and Tsui (2015), an automatic data collection approach with high level systems/technologies and networking sensors such as RFID brings new challenges. They further elaborate that these challenges could be summarized from the horizontal and vertical dimensions. The horizontal dimensions indicate the dynamics of big data, which means the interaction and interlinking features of data among the manufacturing, logistics, and retailing phases. The vertical dimension describes the characteristics of big data, which are highlighted as the "5Vs" – volume, velocity, variety, verification, and value (Hauang et al., 2015). In recent times there have been extensive discussions in both enterprise industrial organizations and academia about a consensus definition of big data (Team, 2011; Grobelnik, 2012). Furthermore, it has been identified that effective and efficient value-adding (V_5) acquisition, storage, development and analysis of big data for enterprise industrial SCM is important in this era and can never be over-emphasized.

The remaining sections of this research paper investigate, discuss and elaborate on the following: first, big data in the perspective of operations/SCM; second, big data applications in operations/SCM; third, various analysis tools for big data in operations/SCM; fourth, the trends and perspective of big data, followed by big data extension; fifth comprises the operational/managerial implications of big data application and analysis in SCM, and finally the paper ends with the conclusion and recommendations of the research.

2. Big data in operations/supply chain management perspective

As already stated in the previous sections of this research paper, the actual definition or an agreed definition of big data has not yet been settled on. However, the aligning definition or what big data really is; is relative and based on the operations of various enterprises industrial organizations. Although there is as yet no agreed definition of big data, many enterprise industrial SCM stakeholders and experts predict that big data will have a positive impact on their operations and activities, enabling them to make more strategic data-oriented and informed decisions. Furthermore, one of the reports from International Data Corporation (IDC), Gantz and Reinsel (2011) predicted that the return-on-investment (ROI) for the big data market would reach $16.1 billion in 2014, thus representing a growth about six-times faster than Information Technology (IT) businesses overall. Therefore, it has become imperative that more effort is put into arriving at a common consensus definition for big data in an operations or supply-chain management perspective to obtain more informed and data-oriented strategic decision making.

Identifying a clear understanding and a common definition of big data in operations or supply-chain management has been long overdue as it is imperative for enterprise SCM (eSCM) stakeholders to work together collaboratively with consistency in definition and terminology. This will enhance efficiency and effectiveness in their Information and Communication Technology (ICT) processes and applications to obtain sustainable competitive advantage. According to Milan (2015), big data provides ample opportunities in SCM as an invaluable instrument for spending analysis in terms of supply-chain risks or measuring supplier performance for senior stakeholders with an accuracy never seen before. Furthermore, Milan stated that big data comes with huge possibilities as well as the ability to drill down and identify credible areas for optimization. Big data has been making huge strides in enterprise industrial circles recently as a prospective and feasible solution to almost every organizational operations challenge facing industrial decision makers today. The research question *(RQ)* here is how

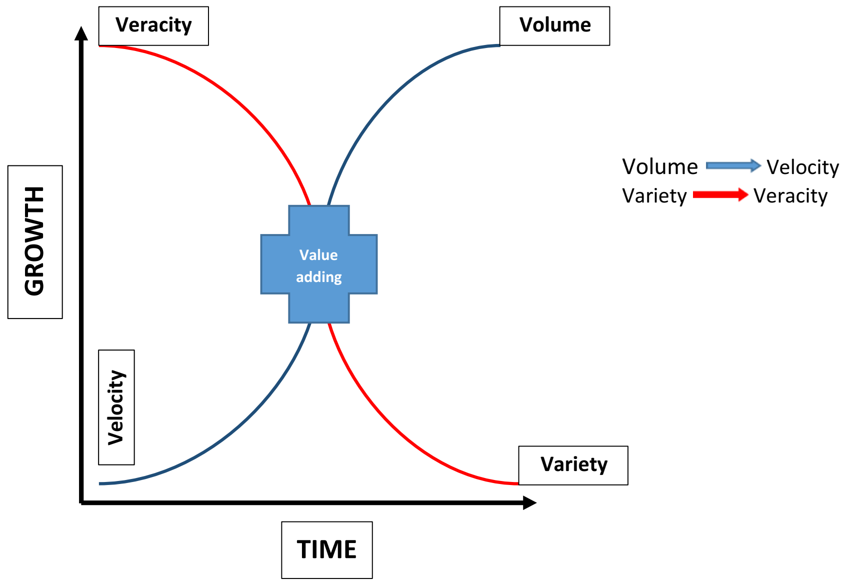

Fig. 1. Modulation of the four Vs of big data – an innovation S-curve model.

operations can or supply-chain management take advantage by adding value *(Value-adding)* efficiently and effectively from the perceived enormous benefits of big data application analytics and implementation processes?

2.1. Existing industrial application concepts: big data in operations/SC management

Big data has been in existence for some time now in many different roles and aspects in many industries, including manufacturing SCs. However, it still appears a relatively untapped asset that industries can still exploit once they decide on or are inclined to apply the right data-mining technologies and techniques. Thus, there are some existing examples of big data applications in industries which did enhance operation processes to some extent. Table 1 outlines a few of the existing concepts and scenarios which did make some impact in specific operation/SC management industrial business use cases (Jeseke, Grüner, & Weiß, 2013).

Adding value to industrial voluminous data/information is imperative for effective and efficient industrial operations/SC management as a strategic asset for enterprise SC competitive advantage. Hence, exploring ways of adding value to the variety and voluminous industrial data generated in a faster analytical approach is imperative in organizational operations/SC management.

3. Various analytical tools for big data implementation processes in operations/supply-chain management

In order to gain a deep understanding of big data, this section will introduce several fundamental technologies that are closely related to big data, including cloud computing, IoT, master database management systems (MDMS), Apache Hadoop, Apache Spark, Map-reduce, etc. Table 2 outlines some of the most widely used "big data" operational tools, their definitions and their implementation benefits:

The Harzing Publish or Perish database analytical tool was employed to assess various items of research published in the area of big data applications between the years 2010 and 2015. Table 3 outlines the various publications on big data applications between those years, including the number of citations from the highest (138) to the lowest (1), including source of publication, etc. Appendix A outlines the remaining publications on big data applications between same years with no (0) citations.

4. Big data applications research publications between 2010 and 2015

The Publish or Perish database software program was employed to retrieve and analyse academic journal citation data from 2010 to 2015 with "Big Data Applications in Operations/Supply-Chain Management" in their titles. This database software program uses

Table 1
Operations and SC Management as a data/information driven business.

#	Concept (use case)	Competitive advantage factors	Attributes
1	Operational efficiency	• Using data to predict crime flashpoints • Operational shift planning in retail stores or manufacturing industries	– Near real-time authentic crime prevention information and transparency – Appropriate staffing for efficient output by improving process quality for good performance
2	Customer experience	– Social influence and analysis for customer retention – Avoiding "out of stock" conditions for customer satisfaction	– Customer loyalty – Precise customer segmentations for optimum approach – Interactive and integrated customer services – Economies of scale and/or "push/pull" bullwhip effect
3	New product development/ introduction NPD/I (New business models)	• New product development and introduction (NPD/I)	– Request/demand for new product lines & business models – New revenue creation and expansion of existing product lines

Table 2
Some big data analytical technologies relevant to supply-chain management.

#	Tools	Definition	Application benefits
1	Cloud computing	Cloud computing analytical tool provides an interesting model for analytics, where solutions can be hosted on the cloud and consumed by customers in a pay-as-you-go fashion (Marcos, Rodrigo, Silvia, Marco, & Rajkumar, 2015)	For the cloud computing analytical tool to be functional as expected, several technical issues must be addressed, such as data management, tuning of models, privacy, data quality, and data currency (Marcos et al., 2015)
2	Master database management system (MDMS)	MDMS analytical tool focuses on processing large volumes of data requiring efficient methods to store, filter, transform, and retrieve value-added data	MDSM provides a much centralised cluster of meta-database systems processing different aspects of the stored, filtered, transformed and retrieved value-added data to enhance more informed and strategic decisions (Addo-Tenkorang, Helo, Shamsuzzoha, Ehrs, & Phuong, 2012)
3	Apache Hadoop	A scalable fault-tolerant distributed system for data storage and processing (open source under the Apache license)	Apache Hadoop enables big data in the form of datasets to be captured, managed, and processed by analytics applications of general computers within an acceptable value-adding scope
4	Map-reduce.	Map-reduce is a distributed fault-tolerant resource management and scheduling application coupled with a scalable data programming abstraction. MapReduce is a simple but powerful programming model for large-scale computing using a large number of clusters of commercial PCs to achieve automatic parallel processing and distribution (Dean & Ghemawat, 2008)	Map-reduce will combine all the intermediate values related to the same key and transmit them to the Reduce function, which further compresses the value set into a smaller set. Map-reduce has the advantage that it avoids the complicated steps for developing parallel applications, e.g. data scheduling, fault-tolerance, and inter-node communications (Min et al., 2014)
5	Apache Cassandra	Apache Cassandra is an open-source distributed database management system which has the capacity to analyse large amounts of data across many product or service servers, providing high availability without any point of failure	Cassandra offers robust support for clusters spanning multiple data-centres, with asynchronous master-less replication allowing low latency operations for all clients. The Apache Cassandra database is said to be the right choice when scalability, high availability and authenticity of value-added data/information without compromising performance is of high importance (Chen & Zhang, 2014)
6	Pentaho	Pentaho is another software platform for big data. It also generates reports from both structured and unstructured large volumes of data. Pentaho serves as a business analytic platform for big data to provide professional services for businessmen with easy access, integration, visualization and exploration of data (Pentaho Business Analytics, 2012)	Pentaho can enable business users to make data-driven decisions that have a positive effect on the performance of their organization. The techniques embeddedin it have several properties, including good security, scalability, and accessibility (Chen & Zhang, 2014)
7	Apache Mahout	Apache Mahout seeks to provide scalable and commercial machine learning techniques for large-scale and intelligent data analysis in industrial applications (Grant, 2009). Examples of these big well-known industries include Google, Amazon, Yahoo!, IBM, Twitter and Facebook. They have implemented scalable machine learning algorithms in their industrial projects. Thus, a significant number of their projects have big data problems and Apache Mahout provides a tool to alleviate the big challenges	Apache Mahout seeks to build a vibrant, responsive, diverse community to facilitate discussions not only in the project itself but also in potential use cases. Hence, its core algorithms include clustering, classification, pattern mining, regression, dimension reduction, evolutionary algorithms and batch-based collaborative filtering, run on top of Hadoop platform via the Map-reduce framework Therefore, the algorithms of Apache Mahout libraries have been well-designed and optimized to have good performance and capabilities. A number of non-distributed algorithms are also contained within it

Google Scholar and Microsoft Academic *(since the release 4.1)*. It presents results which are available on-screen and could also be copied to the Windows clipboard *(for pasting into other applications such MS Excel and similar application)* or saved to a variety of output formats *(for future reference or further analysis)*. This software tool is designed to empower individual academics in presenting a significant case for research impact to its best advantage. Table 3 illustrates the on-screen search results for "Big Data in Applications Operations/Supply-Chain Management" and is exported to MS Excel application for better presentation in the form of a table.

Table 3 illustrates existing and trending research within the theme of "Big Data Applications in Operations/Supply-Chain Management", indicating the impact in this research area. The most cited paper is already in excess of 138 citations (Title: Data-intensive applications, challenges, techniques and technologies: A survey on Big Data; Authors: CLP Chen and CY Zhang; Year of publication: 2014; Publisher: Elsevier). The following section elaborates further on the taxonomy of this literature and more on big data application in operations/SC management focusing on the value-adding competitive advantage of the 5Vs of big data.

5. Literature taxonomy on big data application in operations/supply-chain management

This section seeks to outline some essential classification themes used to review the existing literature and/or studies already available on "big data" application in operations or supply chain Management (SCM). Thus, this section will focus on the taxonomy of the five main attributes of big data application in SCM, namely the 5Vs of big data, which comprise the following:

a. *Big data acquisition sources in SCM:* Big data acquisitions in SCM are from a *variety* of sources in the SC. These sources include the upstream source, which is the suppliers' side, through the intermediate stream source, which is the manufacturers' and consolidation points or warehousing side, and finally the downstream side, which is the logistics and distribution and/or retail side.
b. *Big data storage in SCM:* There are different ways and forms of storing the *voluminous* big data generated in industrial SCs. A structured modelled rational database management system (RDBMS) of auxiliary systems such as servers and database management systems are the classically known data storage equipment employed to look up, analyse, manage and store the huge amount of data generated in a SC. Furthermore, big data storage implies the storage and effective management of voluminous data-clusters in a more value-adding manner, that is, in a more reliable and real-time accessible way. Thus, these data-cluster storage systems or equipment include Direct Attached Storage (DAS) – different types hard-disks/hard-drives which are directly attached to the DBMS and Network Storage (NS) and come in two forms – Network Attached Storage (NAS) and Storage Area Network (SAN). Network storage data-cluster storage

Table 3
Harzing Publish or Perish publication list of big data applications with citations.

Cites	Authors	Title	Year	Publisher
138	CLP Chen, CY Zhang	Data-intensive applications, challenges, techniques and technologies: A survey on big data	2014	Elsevier
72	P Costa, A Donnelly, A Rowstron...	Camdoop: exploiting in-network aggregation for big data applications	2012	dl.acm.org
65	G Wang, TS Ng, A Shaikh	Programming your network at run-time for big data applications	2012	dl.acm.org
41	GH Kim, S Trimi, JH Chung	Big-data applications in the government sector	2014	dl.acm.org
25	S Amer-Yahia, AH Doan, J Kleinberg...	Crowds, clouds, and algorithms: exploring the human side of big data applications	2010	dl.acm.org
25	Y Zhao, J Wu, C Liu	Dache: data aware caching for big-data applications using the MapReduce framework	2014	ieeexplore.ieee.org
21	W Dou, X Zhang, J Liu, J Chen	HireSome-II: Towards privacy-aware cross-cloud service composition for big data applications	2015	ieeexplore.ieee.org
19	S Meng, W Dou, X Zhang, J Chen	KASR: A keyword-aware service recommendation method on MapReduce for big data applications	2014	ieeexplore.ieee.org
17	B Baesens	Analytics in a big data world: The essential guide to data science and its applications	2014	John Wiley & Sons
16	E Barbierato, M Gribaudo, M Iacono	Performance evaluation of NoSQL big-data applications using multi-formalism models	2014	Elsevier
16	A Weichselbraun, S Gindl, A Scharl	Enriching semantic knowledge bases for opinion mining in big data applications	2014	Elsevier
14	H Zou, Y Yu, W Tang, HWM Chen	Flex analytics: a flexible data analytics framework for big data applications with I/O performance improvement	2014a	Elsevier
13	A Zimmermann, M Pretz, G Zimmermann...	Towards service-oriented enterprise architectures for big data applications in the cloud	2013	ieeexplore.ieee.org
12	Y Bu, V Borkar, G Xu, MJ Carey	A bloat-aware design for big data applications	2013	dl.acm.org
12	F Muhtaroglu, S Demir, M Obali...	A business model canvas perspective on big data applications	2013	ieeexplore.ieee.org
9	Z Jia, R Zhou, C Zhu, L Wang, W Gao, Y Shi...	The implications of diverse applications and scalable data sets in benchmarking big data systems	2014	Springer
8	S Tanakamaru, K Takeuchi	Unified solid-state-storage architecture with NAND flash memory and re-RAM that tolerates 32× higher BER for big-data applications	2013	ieeexplore.ieee.org
7	E Zahavi, I Keslassy, A Kolodny	Distributed adaptive routing for big-data applications running on data centre networks	2012	dl.acm.org
7	H Zou, Y Yu, W Tang, HM Chen	Improving I/O performance with adaptive data compression for big data applications	2014b	ieeexplore.ieee.org
7	E Barbierato, M Gribaudo, M Iacono	Modelling apache hive based applications in big data architectures	2013	dl.acm.org
7	K Nguyen, K Wang, Y Bu, L Fang, J Hu...	Facade: A compiler and runtime for (almost) object-bounded big data applications	2015	dl.acm.org
7	J Wang, D Crawl, I Altintas, W Li	Big data applications using workflows for data parallel computing	2014	scitation.aip.org
6	A Castiglione, M Gribaudo, M Iacono...	Modelling performances of concurrent big data applications	2014	Wiley Online Library
5	CH Nadungodage, Y Xia, JJ Lee...	GPU accelerated item-based collaborative filtering for big-data applications	2013	ieeexplore.ieee.org
5	LY Yuan, L Wu, JH You, Y Chi	Rubato DB: A highly scalable staged grid database system for OLTP and big data applications	2014	dl.acm.org
5	Z Bi, D Cochran	Big data analytics with applications	2014	Taylor & Francis
5	C Jardak, P Mähönen, J Riihijärvi	Spatial big data and wireless networks: experiences, applications, and research challenges	2014	ieeexplore.ieee.org
4	Y Chan, I Gray, A Wellings, N Audsley	Exploiting multicore architectures in big data applications: The JUNIPER approach	2014	
4	C Liu, X Zhang, C Liu, Y Yang, R Ranjan...	An iterative hierarchical key exchange scheme for secure scheduling of big data applications in cloud computing	2013	ieeexplore.ieee.org
4	GC Fox, S Jha, J Qiu, A Luckow	Towards an understanding of facets and exemplars of big data applications	2014	cgl.soic.indiana.edu
4	L Mashayekhy, MM Nejad, D Grosu, Q Zhang, W Shi	Energy-aware scheduling of map-reduce jobs for big data applications	2014	ieeexplore.ieee.org
3	S Barahmand...	Benchmarking correctness of operations in big data applications	2014	ieeexplore.ieee.org
3	S Hong	Social network world and big data applications	2013	
3	A Suresh, G Gibson, G Ganger	Shingled magnetic recording forbig data applications	2012	pdl.cmu.edu
3	L Borovick, RL Villars	The critical role of the network in big data applications	2012	3c3cc.com
3	J Chen, PC Roth, Y Chen	Using pattern-models to guide SSD deployment for big data applications in HPC systems	2013	ieeexplore.ieee.org
3	L Wu, L Yuan, J You	Survey of large-scale data management systems for big data applications	2015	Springer
3	E Feller, L Ramakrishnan, C Morin	Performance and energy efficiency of big data applications in cloud environments: a hadoop case study	2015	Elsevier
3	P Düben, J Schlachter, S Yenugula...	Opportunities for energy efficient computing: a study of inexact general purpose processors for high-performance and big-data applications	2015	dl.acm.org
3	WC Hu, N. Kaabouch	Big data management, technologies and applications	2014	books.google.com
2	CG Chute	Obstacles and options for big-data applications in biomedicine: The role of standards and normalizations	2012	ieeexplore.ieee.org
2	P Lu, L Zhang, X Liu, J Yao, Z Zhu	Highly efficient data migration and backup for big data applications in elastic optical inter-data-centre networks	2015	ieeexplore.ieee.org
2	A De la Rosa Algarın...	An approach to facilitate security assurance for information sharing and exchange in big data applications	2013	books.google.com
2	H Jiang, ZL Ren, LM Nie	Software engineering issues in mobile big data applications	2014	
2	A Hayler	big data applications bring new database choices, challenges	2012	
2	S Ryu	Book review: Big data management, technologies and applications	2014	synapse.koreamed.org
2	C Jie	Cloud storage technology and applications for big data [J]	2012	en.cnki.com.cn
2	W Wei, D Jiang, J Xiong, M Chen	Exploring opportunities for non-volatile memories in big data applications	2014	Springer
2	P Dugan, J Zollweg, H Glotin, M Popescu, D Risch...	High Performance Computer Acoustic Data Accelerator (HPC-ADA): A new system for exploring marine mammal acoustics for big data applications	2014	sis.univ-tln.fr

Table 3 (*continued*)

Cites	Authors	Title	Year	Publisher
2	DP Robinson, REH Tappenden	A flexible ADMM algorithm for big data applications	2015	arxiv.org
2	S Park, K Bong, D Shin, J Lee, S Choi…	4.6 A1. 93TOPS/W scalable deep learning/inference processor with tetra-parallel MIMD architecture for big-data applications	2015	ieeexplore.ieee.org
1	M Chen, S Mao, Y Zhang, VCM Leung	Big data applications	2014	Springer
1	A Affelt	The accidental data scientist: Big data applications and opportunities for librarians and information professionals	2015	cds.cern.ch
1	JL Aron, B Niemann	Sharing best practices for the implementation of big data applications in government and science communities	2014	ieeexplore.ieee.org
1	R Casado	Lambdoop, a framework for easy development of big data applications	2013	
1	L Xu	Scalable file systems and operating systems support for big data applications	2014	digitalcommons. unl.edu
1	NS Bhosale, SS Pande	A survey of recommendation systems for big data applications	2015	ciitresearch.org
1	Z Liu	Research of performance test technology for big data applications	2014	ieeexplore.ieee.org
1	EK Karuppiah, YK Kok, K Singh	A middleware framework for programmable multi-GPU-based big data applications	2015	Springer
1	T Vanhove, G Van Seghbroeck…	Live data store transformation for optimizing big data applications in cloud environments	2015	ieeexplore.ieee.org
1	S Scardapane, D Wang, M Panella	A decentralized training algorithm for Echo State Networks in distributed big data applications	2015	Elsevier
1	A Akusok, KM Bjork, Y Miche, A Lendasse	High performance extreme learning machines: a complete toolbox for big data applications	2015	ieeexplore.ieee.org
1	L Sztandera	Computational intelligence in business analytics: Concepts, methods and tools for big data applications	2014	Pearson Education
1	S Zillner, N Lasierra, W Faix, S Neururer	User needs and requirements analysis for big data healthcare applications	2014	big-project.eu
1	S Bardhan, D Menasce	A contention aware hybrid evaluator for schedulers of big data applications in computer clusters	2014	ieeexplore.ieee.org
1	D Seo, S Shin, Y Kim, H Jung, S Song	Dynamic Hilbert Curve-based B+-Tree to manage frequently updated data in big data applications	2014	lifesciencesite.com
1	H Eichelberger, K Schmid	Resource-optimizing adaptation for big data applications	2014	dl.acm.org
1	KC Li, H Jiang, LT Yang, A Cuzzocrea	Big Data: Algorithms, analytics and applications	2015	CRC Press
1	S Zillner, S Neururer	Technology roadmap development for big data healthcare applications	2014	Springer
1	J Ferrarons, M Adhana, C Colmenares…	PRIMEBALL: a parallel processing framework benchmark for big data applications in the cloud	2014	Springer
1	A Cheptsov	HPC in big data age: An evaluation report for Java-Based data-intensive applications implemented with Hadoop and Open MPI	2014	dl.acm.org
1	KVN Rajesh	Big data analytics: Applications and benefits	2013	search. proquest.com
1	B Laub, C Wang, K Schwan, C Huneycutt	Towards combining online and offline management for big data applications	0	
1	Y Chan, A Wellings, I Gray, N Audsley	On the locality of Java 8 Streams in real-time big data applications	2014	dl.acm.org
1	PG Popescu, EI Sluşanschi, V Iancu…	A new upper bound for Shannon entropy. A novel approach in modelling of big data applications	2014	Wiley Online Library
1	D Du, A Li, L Zhang, H Li	Review of the applications and the handling techniques of big data in Chinese realty enterprises	2014	Springer
1	LEB Villalpando, A April, A Abran	Performance analysis model for big data applications in cloud computing	2014	Springer
1	F Xhafa, L Barolli, A Barolli, P Papajorgji	Modelling and processing for next-generation big data technologies: With applications and case Studies	2014	books.google.com

Harzing Publish or Perish Software analytical tool [Run on 18th October 2015 at 11:24 pm].

systems like NAS and SAN are both directly attached to the network, thus enabling a unified network interface platform for real-time data sharing and accessibility. SAN network storage provides a much better scalable and bandwidth data frequency accessibility and it is a more independent network storage system (e.g., cloud computing data storage system).

c. *Big data analysis in SCM:* Big data analysis for value addition has seen a number of big data analytical processing tools, which include a few mentioned in this research paper in Table 1, such as: Apache Hadoop, Cloud computing, IoT, MDBMS and Map-reduce, among others. These listed analytical tools are generic tools embodying sub-analytical tools which may have much better processing power and the capability of achieving *Veracious* data and/or information for informed strategic decisions. Big data analysis could be either performed in real-time, where data/information changes occur constantly, or in an offline mode, where there are no constant changes in the stored data/information but where the results of analysis are expected in a very short time.

d. *Big data application in SCM:* This research specifically attempts to focus on big data application in operations or SCM. Furthermore, the research also investigates the trends and perspectives of big data in this specific area and attempts to recommend a feasible "big data II" or big data IoT-value-adding framework for effective and efficient application of big data in industrial SCM, thus enhancing the *Velocity* of the required data analysis by providing an enabling platform for analysing big date for value-adding.

e. *Big data value-adding in SCM:* Big data analysis and application are the final and most essential stages of big data *Value-adding*. These stages can provide enormous and useful value by enabling informed and strategic decision-making, thus enhancing the application flow *(Velocity)* and *Veracity*, combining to form *Value-adding* from the strategic application of big data.

Table 4 outlines the references used in this review paper. The reference outline is further clustered into sub-themes reflecting the 5Vs of big data grouped into five big data taxonomy themes reviewed and discussed extensively in this paper. The references were correlated or allocated to the 5Vs of big data sub-themes by means of the titles or abstract contents of the references. These allocations may inevitably consist of a few errors of misplaced allocations; however, extreme care was taken in order to reduce any misplacement to the barest minimum.

5.1. Trends and perspective – big data and cloud computing

Big data research surfaced in the 1970s but has seen an explosion of publications since 2008. Although the term "big data" is commonly associated with computer science, research shows that it is applied to many different disciplines, including earth, health, engineering, arts and humanities and environmental sciences. Moreover, mainframe computer systems are fading out with the increase in data volume with there is a quest for storage and processing space. This has constantly motivated further and continuous research into big data trends and perspectives and explains how effectively the area has evolved over the years. Fig. 2 illustrates some significant findings by an Elsevier research trends special issue on big data in 2012.

Big data is an essential attribute of the computation-intensive operation and analytics of the storage capacity of a cloud computational system. The primary goal of a cloud computing system is to use voluminous computing and storage resources under concentrated operational management, in order to provide big data applications with veracious computing capacity. Thus, cloud computing analytics provides solutions for the storage and processing of big data. Hence, the emergence of big data has also increased the advancement and operational expansion of cloud computing. Cloud computing virtual storage technology can effectively analyse and manage big data by means of parallel computing capacity to improve the efficiency of big data acquisition and processing. Furthermore, although there are also numerous similar operational and analytical technologies in cloud computing eminent in big data, there are some differences, including the following (Min et al., 2014):

- Cloud computing systems transform the IT architecture, while big data influences the operational decision-making processes.
- Big data depends on cloud computing as the foundation for smooth analytical operation.

Table 4
Literature references with detailed taxonomy themes on big data applications in operations/SCM.

#	Big data taxonomy themes	Sub-theme (the 5Vs)	References
1	Big data acquisition sources in SCM	Variety	Addo-Tenkorang et al. (2012), Affelt (2015), Amer-Yahia, Doan, and Kleinberg (2010), Atzori et al. (2010), Chan, Gray, Wellings, and Audsley (2014a), Chan, Wellings, Gray, and Audsley (2014b), Chen and Zhang (2014), Grobelnik (2012), Hayler (2012), Hong (2013), Janusz (2013), Jardak et al. (2014), Jiang, Ren, and Nie (2014), Karuppiah, Kok, and Singh (2015), Min et al. (2014), Richard et al. (2011), Ryu (2014), Scardapane, Wang, and Panella (in press), Sagirouglu and Sinanc (2013), Sztandera (2014), Tanakamaru, Doi, and Takeuchi (2013), Team (2011), Uckelmann et al. (2011), Wang, Ng, and Shaikh (2012), Wei, Jiang, Xiong, and Chen (2014), Xu (2014), Yuan, Wu, You, and Chi (2013), Zahavi, Keslassy, and Kolodny (2012), Zhao, Wu, and Liu (2014), and Zimmermann et al. (2013)
2	Big data storage in SCM	Volume	Atzori et al. (2010), Addo-Tenkorang et al. (2012), Bardhan and Menasce (2014), Boos et al. (2013), Chan, Gray, Wellings, and Audsley (2014a), Chen and Zhang (2014), Chen, Roth, and Chen (2013), Cheptsov (2014), Chute (2012), Dugan et al. (2014), Grobelnik (2012), Hayler (2012), Hu and Kaabouch (2014), Janusz (2013), Karuppiah et al. (2015), Laub, Wang, Schwan, and Huneycutt (2014), Lu, Zhang, Liu, Yao, and Zhu (2015), Park et al. (2015), Richard et al. (2011), Tanakamaru et al. (2013), Vanhove, Van Seghbroeck, Wauters, and De Turck (2015), Witlox (2015), Wu, Yuan, and You (2015), Yuan et al. (2013), Ngai, Moon, Riggins, and Yi (2008)
3	Big data analysis in SCM	Veracity	Algarin et al. (2013), Akusok, Bjork, Miche, and Lendasse (2015), Aron and Niemann (2013), Atzori et al. (2010), Baesens (2014), Barahmand and Ghandeharizadeh (2014), Barbierato et al. (2013), Barbierato et al. (2014), Bardhan and Menasce (2014), Bhosale and Pande (2015), Bi and Cochran (2014), Boos et al. (2013), Borovick and Villars (2012), Castiglione, Gribaudo, Iacono, and Palmieri (2015), Chen and Zhang (2014), Chen et al. (2013), Chute (2012), Dean and Ghemawat (2008), Dou, Zhang, Liu, and Chen (2015), Du, Li, Zhang, and Li (2014), Düben et al. (2015), Eichelberger and Schmid (2014), Feller, Ramakrishnan, and Morin (2015), Hu and Kaabouch (2014), Intel IT Centre – Peer Research (2012), Jia et al. (2014), Kaushik (2015), Kees et al. (2015), Kortuem et al. (2010), Li, Jiang, Yang, and Cuzzocrea (2015), Liu et al. (2013), Lu et al. (2015), Mashayekhy, Nejad, Grosu, Zhang, and Shi (2014), Meng, Dou, Zhang, and Chen (2014), Muhtaroglu, Tubitak-Bilgem, Demir, Obali, and Girgin (2013), Nadungodage, Xia, Lee, Lee, and Park (2013), Park et al. (2015), Popescu, Slușanschi, Iancu, and Pop (2014), Rajesh (2013), Robinson and Tappenden (2015), Ryu (2014), Seo, Shin, Kim, Jung, and Song (2014), Suresh, Gibson, and Ganger (2012), Sztandera (2014), Tanakamaru et al. (2013), Vanhove et al. (2015), Villalpando, April, and Abran (2014), Waller et al. (2013), Wamba, Akter, Edwards, Chopin, and Gnanzou (in press), Wang et al. (2012), Wang, Crawl, Altintas, and Li (2014), Xhafa, Barolli, Barolli, and Papajorgji (2014), Zahavi et al. (2012), Zhao et al. (2014), Zillner and Neururer (2014), Zillner, Lasierra, Faix, and Neururer (2014), Zimmermann et al. (2013), Zou, Yu, Tang, and Chen (2014a), and Zou, Yu, Tang, and Chen (2014b)
4	Big data application in SCM	Velocity	Affelt (2015), Akusok et al. (2015), Algarin et al. (2013), Amer-Yahia et al. (2010), Aron and Niemann (2013), Baesens (2014), Barahmand and Ghandeharizadeh (2014), Barbierato et al. (2013), Barbierato et al. (2014), Bardhan and Menasce (2014), Bhosale and Pande (2015), Bi and Cochran (2014), Boos et al. (2013), Borovick and Villars (2012), Bu, Borkar, Xu, and Carey (2013), Casado (2013), Castiglione et al. (2015), Chan et al. (2014a), Chan et al. (2014b), Chen and Zhang (2014), Chen et al. (2014), Cheptsov (2014), Chute (2012), Costa (2012), Dean and Ghemawat (2008), Dou et al. (2015), Du et al. (2014), Düben et al. (2015), Dugan et al. (2014), Fox, Jha, Qiu, and Luckow (2014), Hong (2013), Hu and Kaabouch (2014), Jardak (2014), Jia et al. (2014), Jie (2012), Kaushik (2015), Kim, Trimi, and Chung (2014), Laub et al. (2014), Li et al. (2015), Liu et al. (2013), Mashayekhy et al. (2014), Meng et al. (2014), Milan (2015), Min et al. (2014), Muhtaroglu et al. (2013), Nadungodage et al. (2013), Nguyen et al. (2015), Park et al. (2015), Popescu et al. (2014), Seo et al. (2014), Sztandera (2014), Tanakamaru et al. (2013), Vanhove et al. (2015), Wang, Ng, and Shaikh (2012), Wang et al. (2014), Wei et al. (2014), Weichselbraun, Gindl, and Scharl (2014), Wu et al. (2015), Yuan et al. (2013), Zahavi et al. (2012), Zimmermann et al. (2013), Ngai and Gunasekaran (2007), Ngai, Hu, Wong, Chen, and Sun (2011)
5	Big data value-adding in SCM	Value-adding	Akusok et al. (2015), Algarin et al. (2013), Amer-Yahia et al. (2010), Aron and Niemann (2013), Bardhan and Menasce (2014), Castiglione et al. (2015), Chen et al. (2013), Dou et al. (2015), Düben et al. (2015), Eichelberger and Schmid (2014), Feller et al. (2015), Ferrarons et al. (2014), Gobble (2013), Gantz and Reinsel (2011), Gartner (2013), Greets and O'Leary (2014), Jia et al. (2014), Jiang et al. (2014), Jie (2012), Karuppiah et al. (2015), Kaushik (2015), Kees et al. (2015), Kortuem et al. (2010), Liu (2014), Manyika et al. (2011), Marcos et al. (2015), Mayer-Schoenberger and Cukier (2013), McKinsey Global Institute (2013), Milan (2015), Muhtaroglu et al. (2013), Rajesh (2013), Rosemann (2014), Uckelmann et al. (2011), Villalpando et al. (2014), Weichselbraun et al. (2014), Xhafa et al. (2014), Zimmermann et al. (2013), Zou et al. (2014a), Zou et al. (2014b)

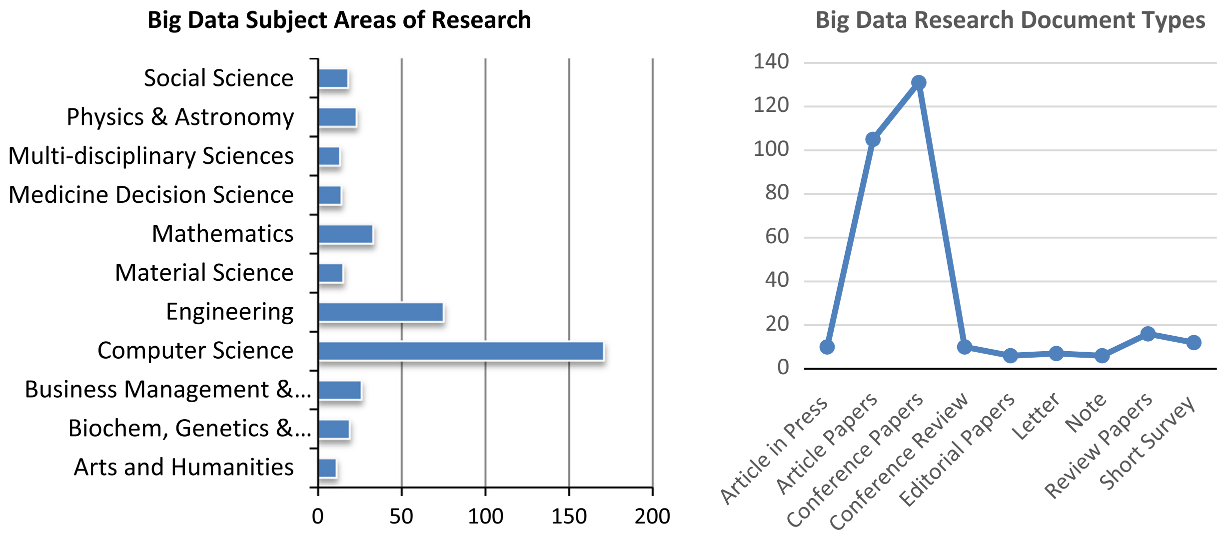

Fig. 2. Big Data Research Areas and Document Types.

- Big data and cloud computing have different target customers. Cloud computing could be open source, but big data is usually not as most of the consolidated data are classified.

According to Min et al. (2014), the main target customers of cloud computing technology and analytical products are chief information officers (CIO), who use cloud computing technologies for advanced IT solutions in operations management or SCM (Gunasekaran & Ngai, 2004), whereas big data is targeting Chief Executive Officers (CEO), who use value-added data/information for making informed strategic business operation decisions. Making informed and strategic decisions positively impacts business operations in a more competitive way. With the collaborative advantage of big data and cloud computing technologies, effective and efficient data analysis and processing would certainly and increasingly complement each other. Cloud computing analytical and operating systems provide system-level resources, whereas big data provides functions similar to those of database management systems for effective and efficient data processing capacity. EMC President Kissinger stated that the application of big data must be based on cloud computing (Chen, Mao, Zhang, & Leung, 2014). Thus, this implies that big data is expected to expand further into the arena of IoT in its next maturity phase. The evolution of big data has been massively propelled by the rapid growth of application demands and cloud computing advancement from virtualized technologies. Therefore, cloud computing not only provides computation and processing for big data, but also itself is a service mode (Min et al., 2014).

6. Big data extension – (big data II/Internet of Things – [IoT])

This section unequivocally and literally refers to IoT as "big data II", and vice versa.

The digitisation of operational activities and Internet-enabled integration of industrial physical objects or products into the networked society is a snapshot of whatIoT seeks to present (Rosemann, 2014). Thus, enabling a powerful integrating network of industrial objects or products of all kinds via RFID sensors and actuators allows the sensing of signals from such object/products, analysing incoming data streams, and in return controlling these objects/products remotely (Zeiler and DHL Solutions and Innovation, 2013; Zhong et al., 2015). Examples include the health care sector in certain developed countries, which remotely manage their patients, smart meters in the energy sector, and predictive maintenance in the manufacturing sector (Kees et al., 2015). Furthermore, Gartner (2013) mentioned that there will be 26 billion smart objects installed by 2020, which will create new market opportunities in excess of 300 billion USD. The McKinsey Global Institute (2013) also identified that the IoT is regarded as one of the most disruptive technologies, with impact on most industrial operations.

The IoT paradigm shift of the information age has produced an enormous amount of networking intelligent agents embedded into various devices and machines in the real world. Such intelligent agents distributed in different fields collect diverse amounts of voluminous data, such as operations, design, production and manufacturing, environmental, geographical, astronomical, and logistical data. Mobile devices, logistics facilities, public facilities, health care systems and home appliances could all be data acquisition equipment in IoT. Quite recently, research has predicted that IoT data would be an integral part of big data by the year 2030 and the required quantity of intelligent agents would reach one trillion, thus making IoT data the most important part of big data, according to the forecast of HP. Also, a report from Intel pointed out that big data in IoT has three features that conform to the normal or general operational big data paradigm:

- Big data of IoT is useful only when it is analysed and processed for value-adding.
- Numerous network points or terminal points generating a variety of data.
- Big data generated by IoT is usually semi-structured or unstructured.

It is clear that industrial operators of IoT realize the enormous potential and essence of the capabilities of big data and it is obvious that the success of IoT is hinged on the effective integration and synchronization of industrial big data and cloud computing systems. Therefore, lately there has been a compelling need to adopt big data in industrial operational processes and product-development principles in order to enhance IoT applications, while the development of big data is already lagging behind in integration with cloud computing. It has been widely recognized that these two technologies are interdependent and should be jointly developed: meaning that the widespread deployment of IoT drives the high growth of data

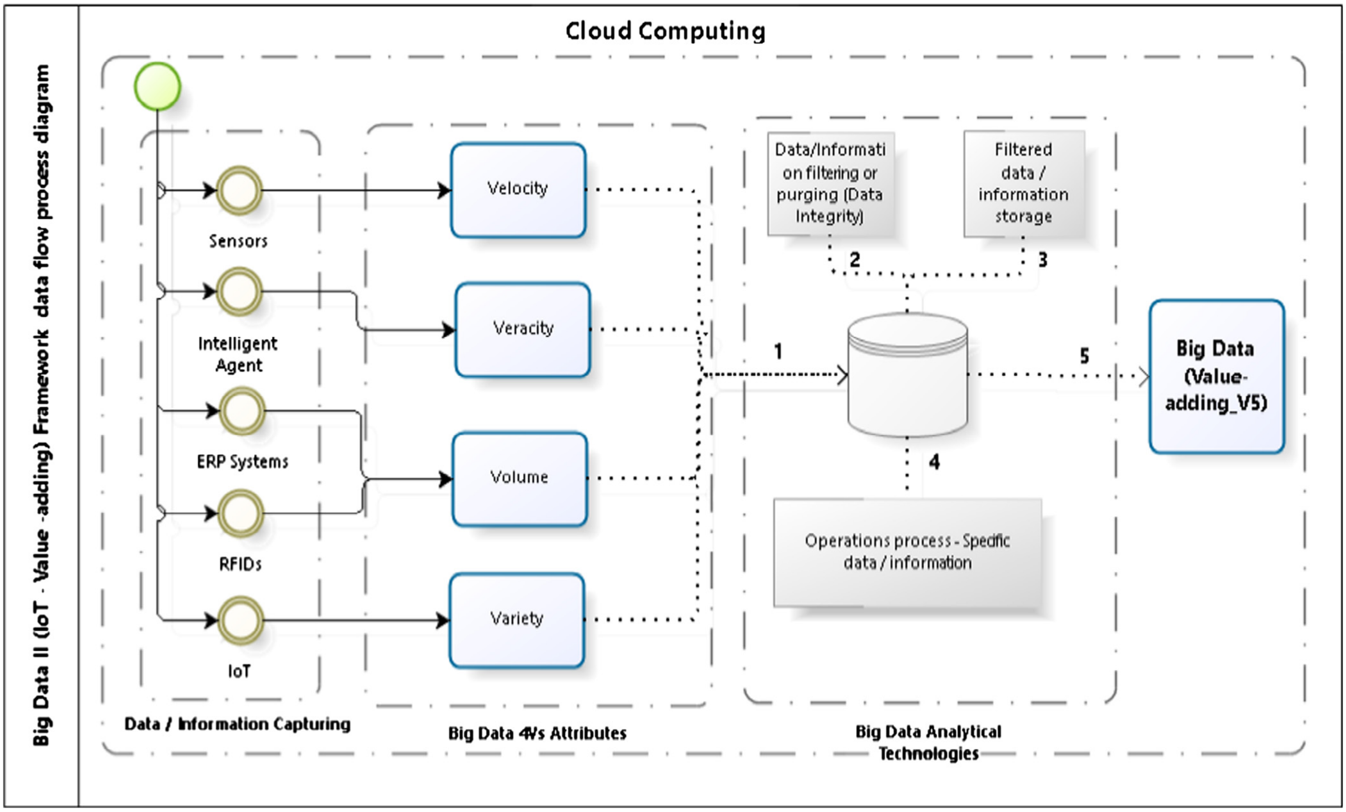

Fig. 3. *"Big data II" (IoT – Value-adding) framework.* (Powered by Bizagi Modeller 2015).

(Min et al., 2014). Kees, Oberländer, Röglinger, and Rosemann (2015) define IoT as the connectivity of physical objects or industrial products, equipped with sensors and actuators, to the Internet via data communication technology, enabling interaction with and/or among these objects or products after having reviewed a number of different definitions in their research, such as Boos, Guenter, Grote, and Kinder (2013), McKinsey Global Institute (2013), Uckelmann, Harrison, and Michahelles (2011).

According to Kees et al. (2015) IoT has been comprehensively discussed in terms of engineering-related challenges (industrial operations and/or manufacturing supply-chain management) (Atzori, Iera, & Morabito, 2010; Kortuem, Kwasar, Fitton, & Sundrammoorthy, 2010), and also from a business-to-business (B2B) perspective (product and services supply-chain management) (Geerts and O'Leary, 2014). The Information Systems (IS) (technology) community has been rather passive with regard to researching the customer-related business implications of IoT. Furthermore, Wamba et al. (2015) have researched how big data can make a big impact: their findings from a systematic review and longitudinal case study show that, despite high operational and strategic impacts, there is a paucity of empirical research to assess the business value of big data for the benefit of industrial operations or SCM. Therefore, this paper attempts to propose a framework for an effective, efficient and sustainable "big data II" for IoT applications in industrial operations or supply-chain management for industrial competitive advantage and innovation in the SC architecture (Gobble, 2013; Waller & Fawcett, 2013). Also the next section in this paper will outline some feasible and sustainable outlines for the expansion of big data to "big data II"/IoT-Value-adding in terms of industrial operational or managerial implications as illustrated in Fig. 3. The illustrated framework in Fig. 3 is further elaborated in detail in the concluding section.

6.1. Managerial implications

The Internet of Things (IoT) according to the findings in this research has come to the forefront in driving the high growth of data both in terms of quantity and category, thus providing the opportunity for the application and development of big data; on the other hand, the application of big data technology to IoT also accelerates the research advances and business models of IoT (Min et al., 2014). Furthermore, IoT can also enable improvement of products and services, customer experience, security, etc., if it is properly harnessed. IoT also has the potential to transform traditional business-to-customer interactions in a way previously not thought of (Kees et al., 2015) when networking sensors such as RFIDS are embedded in a variety of electronic devices and/or machines to communicate and exchange data or information in real-time and in a real world activity (Zhong et al., 2015). IoT thus represents a creative disruption, something that begins to overthrow existing processes and technologies and bring forth a completely new way of working and managing electronic network activities (Kaushik, 2015). According to Kees et al. (2015) IoT is widely regarded as one of the most disruptive technologies as it integrates Internet-enabled physical objects into the networked society and makes these objects increasingly autonomous partners in digitised value chains. This is best implemented with high level networking sensors such as RFID, thus indicating that the applications of RFID technology are indeed on the increase and are bound to offer new avenues for growth and new opportunities on the emerging frontier of effective and efficient operations/SC management. RFID technology has existed for many years but has only recently emerged as the technology used in supply chains (Ngai and Gunasekeran, 2007).

Appendix A

Harzing Publish or Perish publication list of big data applications with (0/no) citations.

Cites	Authors	Title	Year	Publisher
0	LF Sikos	Big Data Applications	2015	Springer
0	M Abdellatif, I Saleh, MB Blake	JPrivacy: A java privacy profiling framework for Big Data applications	2014	ieeexplore.ieee.org
0	D Oostra, T Hunt, LH Chambers…	NASA and GLOBE Connect K-12 Students to NGSS with Big Data Applications	2014	adsabs.harvard.edu
0	D Liu, S Xu, Z Cui	Using client-side access partitioning for data clustering in big data applications	2014	ieeexplore.ieee.org
0	N Mohamed, J Al-Jaroodi	Real-time big data analytics: Applications and challenges	2014	ieeexplore.ieee.org
0	A Agrawal	Deploying Big Data Applications to the Cloud	2015	ideals.illinois.edu
0	H Chen, B Bhargava, F Zhongchuan	Multilabels-Based Scalable Access Control for Big Data Applications	2014	ieeexplore.ieee.org
0	TMS MEKALARANI, M KALAIVANI	RECOMMENDATION METHOD ON HADOOP AND MAPREDUCE FOR BIG DATA APPLICATIONS	0	
0	V Fernandez, V Méndez…	BigDataDIRAC: deploying distributed Big Data applications	2015	ieeexplore.ieee.org
0	J Lofstead, I Jimenez, C Maltzahn…	POSTER: An innovative storage stack addressing extreme scale platforms and Big Data applications	2014	ieeexplore.ieee.org
0	Z Yin, C Min, L Xiaofei	Big Data Applications: A Survey	2013	en.cnki.com.cn
0	SMD MUJEEB, LK NAIDU	A Relative Study on Big Data Applications and Techniques	0	
0	AM Nagrale, AP Pande	User Preferences-based Recommendation System for Services Using Map Reduce Approach for Big Data Applications	2015	academicscience.co.in
0	NS Bhosale, SS Pande	A Service Recommendation Method based on User Preferences for Big Data Applications	0	
0	C Hesselman, J Jansen, M Wullink, K Vink, M Simon	A privacy framework for 'DNS big data' applications	0	
0	C Chen, D Yang, S Wang, D Yang	Big Data Applications in Power Industry	2015	atlantis-press.com
0	T Vanhove, GV Seghbroeck, T Wauters…	Tengu: an Experimentation Platform for Big data Applications	2015	ieeexplore.ieee.org
0	EE Durham, A Rosen…	A model architecture for Big Data applications using relational databases	2014	ieeexplore.ieee.org
0	F Rossi, V Saraswat	Constraint Programming Languages for Big Data Applications	0	
0	R Luijten, D Pham, R Clauberg…	4.4 Energy-efficient microserver based on a 12-core 1.8 GHz 188K-CoreMark 28nm bulk CMOS 64b SoC for big-data applications with 159 GB/S/L …	2015	ieeexplore.ieee.org
0	AS Harsoor, A Patil	FORECAST OF SALES OF WALMART STORE USING BIG DATA APPLICATIONS	0	
0	R Ranjan, L Wang, AY Zomaya…	Recent advances in autonomic provisioning of big data applications on clouds	2015	ieeexplore.ieee.org
0	GB Achary, P Venkateswarlu…	Importance of HACE and Hadoop among Big data Applications	2015	internationaljournalofresearch.org
0	WJ Xu, CD Zhao, HP Chiang, L Huang…	The RR-PEVQ algorithm research based on active area detection for big data applications	2015	Springer
0	F Korangy, H Ghasemzadeh, M Arjmandi…	System and method providing hierarchical cache for big data applications	2014	Google Patents
0	L Dolberg, J François, S Rahman…	Network Configuration and Flow Scheduling for Big Data Applications	2015	CRC Press
0	W Abbes, Z Kechaou, AM Alimi	Toward a Framework for Improving the Execution of the Big Data Applications	2015	Elsevier
0	T Raynaud, R Haque, H Ait-kaci	CedCom: A high-performance architecture for Big Data applications	2014	ieeexplore.ieee.org
0	SL See	Big Data Applications: Adaptive User Interfaces to Enhance Managerial Decision Making	2015	dl.acm.org

(*continued on next page*)

Appendix A (*continued*)

Cites	Authors	Title	Year	Publisher
0	H Ke, P Li, S Guo, M Guo	On Traffic-Aware Partition and Aggregation in MapReduce for Big Data Applications	0	
0	Y Zhenshan, L Ying, N DOUAY	Opportunities and limitations of big data applications to human and economic geography: the state of the art	2015	progressingeography.com
0	C Brugger, C de Schryver, N Wehn	Heterogeneous Platforms for Big Data Applications	2014	
0	J Kleinberg, N Koudas	Crowds, Clouds, and Algorithms: Exploring the Human Side of "Big Data" Applications	0	
0	I Mytilinis, D Tsoumakos, V Kantere, A Nanos, N Koziris	I/O Performance Modelling for Big Data Applications over Cloud Infrastructures	0	
0	D Dang, Y Liu, X Zhang, S Huang	A Crowdsourcing Worker Quality Evaluation Algorithm on MapReduce for Big Data Applications	0	
0	J Kim, ST Hwang	Approach to Big Data Applications on Cloud System	2015	onlinepresent.org
0	Z Zdravev, B Delipetrev	High-Performance Modelling and Simulation for Big Data Applications (cHiPSet)	2015	eprints.ugd.edu.mk
0	S Wang, X Wang, J Huang, R Bie, X Cheng	Analysing the potential of mobile opportunistic networks for big data applications	2015	ieeexplore.ieee.org
0	Z Ji	Applications Analysis of Big Data Analysis in the Medical Industry	2015	sersc.org
0	B Bhargava, I Khalil, R Sandhu	Securing Big Data Applications in the Cloud	2014	computer.org
0	R Chauhan, H Kaur	A Spectrum of Big Data Applications for Data Analytics	2015	Springer
0	DP Acharjya, S Dehuri, S Sanyal	Computational Intelligence for Big Data Analysis: Frontier Advances and Applications	2015	books.google.com
0	MAA da Silva, A Sadovykh, A Bagnato…	Taming the Complexity of Big Data Multi-Cloud Applications with Models	2014	ceur-ws.org
0	KNKWY Bu, LFJHG Xu	FACADE: A Compiler and Runtime for (Almost) Object-Bounded Big Data Applications	2015	ics.uci.edu
0	D Wang, Z Han	Sublinear Algorithms for Big Data Applications	2015	Springer
0	EE Durham, A Rosen…	Optimization of relational database usage involving Big Data a model architecture for Big Data applications	2014	ieeexplore.ieee.org
0	P Bellavista, A Corradi, A Reale…	Priority-Based Resource Scheduling in Distributed Stream Processing Systems for Big Data Applications	2014	ieeexplore.ieee.org
0	PK Akulakrishna, J Lakshmi…	Efficient Storage of Big-Data for Real-Time GPS Applications	2014	ieeexplore.ieee.org
0	N ANUSHA, P VINDHYA, T SUJILATHA	Towards Keyword Based Recommendation for Big Data Applications	2015	ijsetr.com
0	L Wu, LY Yuan, JH You	Survey and Taxonomy of Large-scale Data Management Systems for Big Data Applications	0	
0	K Fountoulakis, R Tappenden	A Flexible Coordinate Descent Method for Big Data Applications	2015	arxiv.org
0	P Jain, S Kohli	Big Data Analysis, Algorithms and Applications: A Survey	0	
0	L Bougé	Managing Consistency for Big Data Applications on Clouds: Tradeoffs and Self-Adaptiveness	2013	Citeseer
0	HE Chihoub	Managing consistency for big data applications: tradeoffs and self-adaptiveness	2013	tel.archives-ouvertes.fr
0	X Zeng, R Ranjan, P Strazdins…	Cross-Layer SLA Management for Cloud-hosted Big Data Analytics Applications	2015	ieeexplore.ieee.org
0	A Türk	UTILIZING QUERY LOGS FOR DATA REPLICATION AND PLACEMENT IN BIG DATA APPLICATIONS	2012	thesis.bilkent.edu.tr
0	LY Yuan, L Wu, JH You, Y Chi	A Demonstration of Rubato DB: A Highly Scalable NewSQL Database System for OLTP and Big Data Applications	2015	dl.acm.org
0	A Ditter, D Fey, T Schon, S Oeckl	On the Way to Big Data Applications in Industrial Computed Tomography	2014	ieeexplore.ieee.org
0	B Chandramouli, J Levandoski, E Vilarinho	ICE: Managing Cold State for Streaming Big Data Applications	0	
0	F Korangy, H Ghasemzadeh, M Arjmandi…	System and method providing marketplace for big data applications	2014	Google Patents

Appendix A (*continued*)

Cites	Authors	Title	Year	Publisher
0	LY Yuan	Performance Evaluation of RubatoDB: A Highly Scalable Staged Grid Database System for OLTP and Big Data Applications	0	
0	R Ranjan, D Georgakopoulos, L Wang	A note on software tools and technologies for delivering smart media-optimized big data applications in the cloud	0	Springer
0	I Chebbi, W Boulila, IR Farah	Big Data: Concepts, Challenges and Applications	2015	Springer
0	P Dugan, J Zollweg, M Popescu, D Risch…	High Performance Computer Acoustic Data Accelerator: A New System for Exploring Marine Mammal Acoustics for Big Data Applications	2015	arxiv.org
0	D Roca Marí	Communication bottleneck analysis on big data applications	2013	upcommons.upc.edu
0	R Buyya	Market-Oriented Cloud Computing and Big Data Applications	0	
0	D Ardagna, I e Bioingegneria, MS Squillante	Special Issue on Performance and Resource Management in Big Data Applications	0	
0	MR Vieira, S Wang	An Approach to Benchmarking Industrial Big Data Applications	2015	books.google.com
0	U Kalim, M Gardner, E Brown…	Poster: Cascaded TCP: BIG Throughput for BIG DATA Applications in Distributed HPC	2012	ieeexplore.ieee.org
0	S Zillner, H Oberkampf, C Bretschneider…	Towards a technology roadmap for big data applications in the healthcare domain	2014	ieeexplore.ieee.org
0	Q Shi, M Abdel-Aty	Big Data applications in real-time traffic operation and safety monitoring and improvement on urban expressways	2015	Elsevier
0	A Cuzzocrea	Aggregation and multidimensional analysis of big data for large-scale scientific applications: models, issues, analytics, and beyond	2015	dl.acm.org
0	L Wang, CA Alexander	Big Data in Medical Applications and Health Care	2015	search.proquest.com
0	ΑΛ Γεωργιάδης	Performance Monitoring And Workload Characterization Of Big Data And Cloud Based Applications On The Intel Scc Manycore Platform	2015	artemis-new.cslab.ece.ntua.gr
0	L Ntaganda, H Kim	Using a Cache Simulator on Big Data Applications	0	
0	JPC Verhoosel, M van Bekkum, FK van Evert	Ontology Matching for Big Data Applications in the Smart Dairy Farming Domain	2011	disi.unitn.it
0	B Chandra, RK Sharma	Fast learning for big data applications using parameterized multilayer perceptron	2014	ieeexplore.ieee.org
0	M Harding, C Lamarche	Sparsity-Based Estimation of a Panel Quantile Count Data Model with Applications to Big Data	2015	paneldataconference2015.ceu.hu
0	S Spicuglia, LY Chen, R Birke…	Optimizing capacity allocation for big data applications in cloud datacenters	2015	ieeexplore.ieee.org
0	J Liu	Fast Data Analysis Framework for Scientific Big Data Applications	2015	repositories.tdl.org
0	N Regola, DA Cieslak, NV Chawla	The Need to Consider Hardware Selection when Designing Big Data Applications Supported by Metadata	0	
0	PR Van Reed	Cell Phone Technology and Big Data Applications in Emergency Evacuations	2015	digitalcommons.apus.edu
0	S Aman, C Chelmis, V Prasanna	Addressing data veracity in big data applications	2014	ieeexplore.ieee.org
0	SE Salim	… JOURNAL OF ENGINEERING SCIENCES & RESEARCH TECHNOLOGY Service Oriented Enterprise Architecture For Processing Big Data Applications In …	0	
0	J Ranjan	Big Data Applications in Healthcare	2014	books.google.com
0	S Wenzel	App 'ification of Enterprise Software: A Multiple-Case Study of Big Data Business Applications	2014	Springer
0	U Kalim, M Gardner, E Brown…	Cascaded TCP: BIG Throughput for BIG DATA Applications in Distributed HPC	2012	ieeexplore.ieee.org
0	N Schot	Feasibility of Raspberry Pi 2 based Micro Data Centers in Big Data Applications	2015	referaat.cs.utwente.nl

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Appendix A (*continued*)

Cites	Authors	Title	Year	Publisher
0	M Mingrui	Big Data Applications in Urban Planning: The Thinking and Practice from BICP	2014	en.cnki.com.cn
0	R Sandhu, SK Sood	Scheduling of big data applications on distributed cloud based on QoS parameters	2015	Springer
0	AM AlMutairi, RAT AlBukhary, J Kar	Security and Privacy of Big Data in Various Applications	2015	sersc.org
0	K De, S Panitkin, D Yu, T Maeno, A Klimentov…	Extending the ATLAS PanDA Workload Management System for New Big Data Applications	2013	cds.cern.ch
0	T Senkova, J Zibuschka	A Cloud-based Component Marketplace Enabling Privacy-friendly Big Data Applications	0	
0	P Sowmiyaa, V Priyadharshini, N Minojini, RK Gayathri	AN EFFICIENT APPROACH ON SPATIAL BIG DATA RELATED TO WIRELESS NETWORKS AND ITS APPLICATIONS	0	
0	KF Li, W Rahayu	Special section on support technology and architecture for networked and distributed applications in big data era	2015	Springer
0	D Robinson, R Tappenden	A Flexible ADMM for Big Data Applications	0	
0	D Dai, Y Chen, D Kimpe, R Ross	Provenance-based object storage prediction scheme for scientific big data applications	2014	ieeexplore.ieee.org
0	NE Oweis, SS Owais, W George, MG Suliman…	A Survey on Big Data, Mining:(Tools, Techniques, Applications and Notable Uses)	2015	Springer
0	Y Shen, Y Li, L Wu, S Liu, Q Wen	Big Data Techniques, Tools, and Applications	2013	books.google.com
0	E Strange	Barriers to the Adoption of Big Data Applications in the Social Sector	2015	CRC Press
0	AR Arhun, AVK Shanthi	An Efficient Personalized Hotel Recommendation System for Big Data Applications	2015	worldofresearches.com
0	A Theissler	BIG DATA APPLICATIONS AND PRINCIPLES First International Workshop, BIGDAP 2014 Madrid, Spain, September 11–12 2014	0	
0	GF Lofstead, I Jimenez, C Maltzahn, Q Koziol, J Bent…	An Innovative Storage Stack Addressing Extreme Scale Platforms and Big Data Applications	2014	osti.gov
0	S Elfayoumy	USING INTELLIGENT AGENTS FOR PERFORMANCE TUNING OF BIG DATA PARALLEL APPLICATIONS	2012	search.proquest.com
0	D Ghersi, WP Anderson	Big Data applications focus of financial interest	2015	… MED PUBL CO LTD LEVEL 2, 26- …
0	S Weddell	The Accidental Data Scientist: Big Data Applications and Opportunities for Librarians and Information Professionals	2015	emeraldinsight.com
0	U Dayal, C Gupta, R Vennelakanti, MR Vieira…	An Approach to Benchmarking Industrial Big Data Applications	2015	Springer
0	C Chen, M Lang, Y Chen	Multilevel Active Storage for big data applications in high performance computing	2013	ieeexplore.ieee.org
0	T Rout, M Garanayak, MR Senapati…	Big data and its applications: A review	2015	ieeexplore.ieee.org
0	HH PARMAR	APPLICATIONS OF BIG DATA IN GOVERNMENT SECTOR	0	
0	L Rodríguez-Mazahua, CA Rodríguez-Enríquez…	A general perspective of Big Data: applications, tools, challenges and trends	2015	Springer
0	B Javadi, B Zhang, M Taufer	Bandwidth Modelling in Large Distributed Systems for Big Data Applications	0	
0	A Cuzzocrea, E Mumolo…	Cloud-based Machine Learning Tools for Enhanced Big Data Applications	2015	ieeexplore.ieee.org
0	C Shangyi	Big Data Applications and Practices of Baidu	2015	j-bigdataresearch.com.cn
0	M Abouelela, M El-Darieby	Scheduling big data applications within advance reservation framework in optical grids	2015	Elsevier
0	P Gölzer, P Cato, M Amberg	Data Processing Requirements of Industry 4.0-Use Cases for Big Data Applications	2015	aisel.aisnet.org
0	Y Marchetti	Solution Path Clustering with Minimax Concave Penalty and Its Applications to Noisy Big Data	2014	statistics.ucla.edu

Appendix A (*continued*)

Cites	Authors	Title	Year	Publisher
0	S Mujawar, S Kulkarni	Big Data: Tools and Applications	2015	search.proquest.com
0	AS Alghamdi, I Ahmad, T Hussain	Big data for C4i systems: goals, applications, challenges and tools	2015	ieeexplore.ieee.org
0	FZ Benjelloun, AA Lahcen…	An overview of big data opportunities, applications and tools	2015	ieeexplore.ieee.org
0	VK Singh, DS Kushwaha, S Singh, S Sharma	Scope of Big Data and Its Applications	0	
0	S Ravada	Big data spatial analytics for enterprise applications	2015	dl.acm.org
0	I You, MR Ogiela, M Hwang	Intelligent technologies and applications for big data analytics	2015	Wiley Online Library
0	DR Kale, SR Todmal	A Survey on Big Data mining Applications and different Challenges	0	
0	YS Jeong, J Ma, LT Yang…	Advanced communication systems for enhanced big data technology and applications	2014	Wiley Online Library
0	KV Rao, MA Ali	SURVEY ON BIG DATA AND APPLICATIONS OF REAL TIME BIG DATA ANALYTICS	2015	ijcea.com
0	L Jianxin	Big data technology: current applications and prospects	2015	telecomsci.com
0	C GUPTA, A FARAHAT, K RISTOVSKI	Analytics-Driven Industrial Big Data Applications (特集 OT と IT の融合: IoT 時代のオペレーション革新)	2015	ci.nii.ac.jp

Harzing Publish or Perish Software Analytical Tool [Run on 18th October 2015 at 11:24 pm].

7. Conclusion and future recommendations

There are quite a number of available big data mining and analytical tools now, including professional and non-professional software, expensive industrial or commercial software, and open source ones. Table 1 outlines some of this industrial and/or open source big data software available to enable and enhance the streamlining of industrial big data in a much more value-adding and sustainable perspective. Although there have been a number of research papers in the area of big data applications attempting to identify and understand the challenges in industrial or supply-chain "big data" applications, effectively implementing big data analytics in real-time and in IoT process is a huge and extremely complex undertaking for most industrial operations. Therefore, it is imperative for industrial management to holistically perform effective and efficient operational assessment of the tasks/processes and re-organize them into smaller and more manageable chunks. This process will streamline and enhance the "Velocity" attribute of huge "Voluminous" big data into a more preferable "Variety" structural attribute and into "Veracious" analytical processes, thus ensuring more sustainable "Value-adding" operational processes. Fig. 3 illustrates the proposed "big data II"/IoT-Value-adding framework flow process in this paper.

This paper recommends that further research is conducted into the real-live industrial implementation of the proposed "big data II"/IoT-Value-adding framework illustrated in Fig. 3. Furthermore, the back-end network integration programming or coding research should be looked into for feasible and successful implementation of the proposed framework. As data and/or information in general and especially industrial operations or supply-chain management data are confidential and sensitive, so the data security aspect of "big data II"/IoT-Value-adding framework could be further investigated for authenticity. Finally, the application of RFID in terms of IoT and specifically its impact on the efficient management of big data applications in operations/SC management in enterprise industrial activities need further investigation.

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